Week 7 TA Session

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Panel Method 2: FE

- A second panel data specification method
- Fixed effects are often unobservable, but excluding them from our estimation might introduce endogeneity problems.
- For a basic panel data fixed effect regression, we have a generic model specification:

$$Y_{it} = X_{it}\beta + \tau D_{it} + \varepsilon_{it} \quad \varepsilon_{it} = \alpha_i + \delta_t + v_{it}$$

- Estimate by:

1. Generating a series of dummies to represent the fixed effects

$$Y_{it} = X_{it}\beta + \tau D_{it} + \sum_{j=1}^{N} 1(i = j) + \epsilon_{it}$$

2. De-meaning all the variables to remove the fixed effects

$$Y - \bar{Y} = (X - \bar{X})\beta + \tau(D - \bar{D}) + (\alpha - \bar{\alpha}) + (\varepsilon - \bar{\varepsilon})$$

Fe Cont.

The error term can be decomposed into three components:

1. Time : δ_t represents the *time-specific and individual-invariant* fixed effect

2. Individual : α_i represents the *individual-specific and time- invariant* fixed effect

Example: Beer and Traffic

Background: The Fatalities is a panel dataset that contains information on traffic deaths and alcohol taxes of various states from year 1982 to 1988. We are interested in how the policy of increasing alcohol taxes will affect the rate of traffic deaths. Let us look at how will our analysis differ when employing the cross-sectional data method vs the panel data method.

- First without FE, just plain reg (cross-sectional)
- Then with state fixed effects, which will control for any time-invariant state differences in traffic fatalities, ie maybe states with and without higher taxes are fundamentally different (panel data)

Cumulative Effects

To capture the treatment effects at different points in time. This is made possible by including a series of indicators of time dummies.

$$Y_{it} = \sum_{s=0}^{S} \tau_s D_{i,t-s} + \alpha_i + \delta_t + X_{it}\beta + v_{it}$$

where s indicates the time when the program is implemented. This models allows us to investigate the lasting effect of a program over different time horizons. The interpretation of the coefficients τ_s should be partial, which means the effect at a given moment holding the effects at other times as constant. Therefore, the cumulative effect should be the summation of all these coefficients.

And more generally, we can even include indicators of pre-treatment periods to test for confounding factors, if any. The estimated coefficients for the pre-treatment time indicators should be **centered around zero** and **suggest no trending**

See pdf for more details*

Example: CC Laws

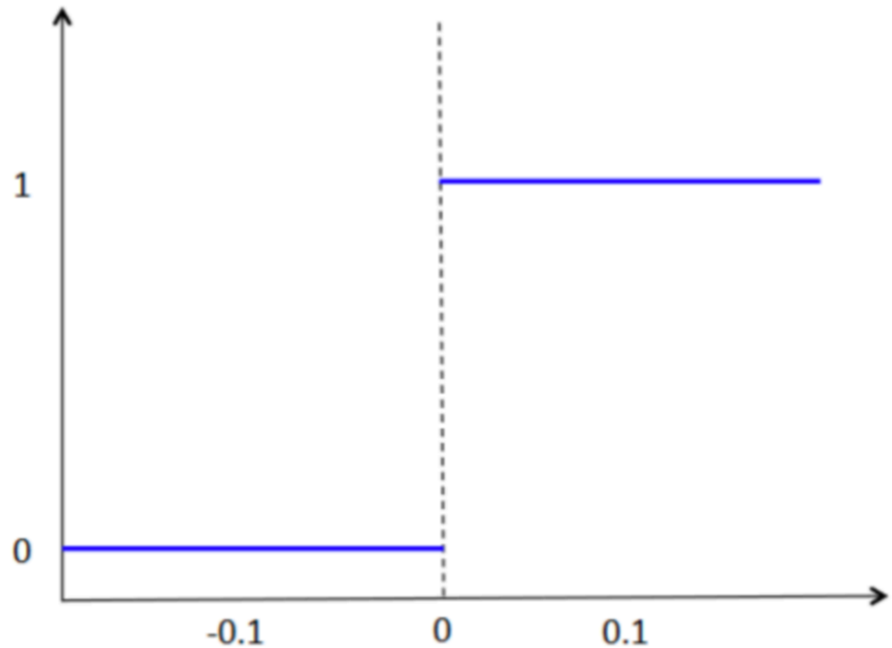
Background: we want to examine the effect of “Carrying a concealed weapon” law on the number of violent crimes.

- Constrain sample to those who up took law in 1990
- Log violent crime
- Control for state and time
- Look for pretreatment centered around 0 and no trending

RDD

- Discrete or continuous variable that includes a cut off or threshold which determines treatment
- Ex: voting on policies (50%), income requirements for gov series etc
- RD allows us to mimic random assignment by looking at unit outcomes just above and just below a cut off point
- If, we can argue that those just above and just below are not meaningfully different

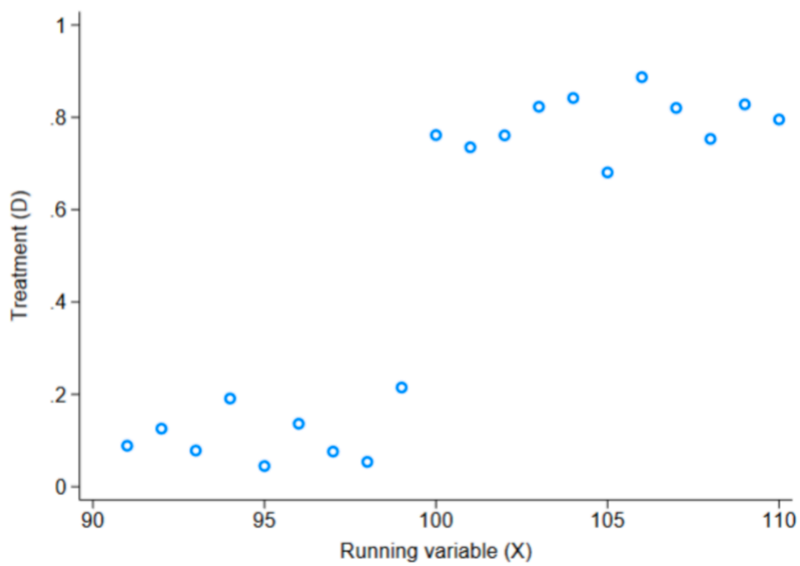
Sharp RDD



- Perfect compliance

$$\Pr(D_i = 1 | X_i \geq c) = 1 \text{ and } \Pr(D_i = 1 | X_i < c) = 0$$

Fuzzy RDD



- Imperfect Compliance

$$\Pr(D_i = 1 | X_i \geq c) - \Pr(D_i = 1 | X_i < c) = k \text{ where } 0 < k < 1$$

- Remainder on sharp rd continue with fuzzy next week

RDD Assumption

- Continuity in Y across the cutoff $E(Y_i(1)|X_i = x)$ and $E(Y_i(0)|X_i = x)$ continuous in x
- Cannot test this, since we don't know counterfactual
- However, graphical tests help support our assumption

RDD Graphical Support

Four Graphical Tests to Support assumption:

1. **Density of Running Variable** - This helps with the argument that there is no manipulability in the running variable. Want to see smooth density across the threshold, this provides evidence that the cutoff is essentially random. Argument against selection bias.

2. **Continuity in Covariates** - This serves as a proxy for continuity in potential outcomes. By observing continuity in the observables across the cut off, we can argue that the discontinuity in Y for treated and untreated is solely from difference in treatment status.

3. **Outcome across Running Variable** - This is a good first check to see if there is potential for using an RD design. This will give a visual idea of whether there is a discontinuous jump between treatment and control groups.

4. **Proportion of Treatment across Running Variable** - This helps determine if our RD design is a fuzzy or sharp RD.

Model for RDD

- Our regression model for estimating the treatment effect within some bandwidth is as follows:

$$Y_i = \alpha + \tau D_i + \beta_1 (X_i - c) + \beta_2 (X_i - c) D_i + \varepsilon_i$$

- $\hat{\tau}^{SRD}$ estimates our LATE - this is what we are generally interested in, note its for values at cutoff
- B1 provides the slope for values below the cutoff
- B2 provides the slope for values above the cutoff 2

IM Example

- Infants below a certain weight receive extra care
- How does this extra care reduce mortality?
- Do we believe infants just above and just below the 1500g cutoff are as good as random?