Regression Discontinuity Design

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Microeconometrics

Winter Term 2012/13
History

- Basic idea goes back to the sixties
- Forgotten for many years
- Rediscovered in the nineties (Angrist/Lavy 1999, Maimonides rule – exploit discontinuity to estimate causal effect of class size on scholastic achievement
- Interpreted as a special case of IV by Angrist/Lavy (selection on unobservables)
- Interpreted as a selection on observables approach by Heckman
- Today: RDD is interpreted as a design
- Intuition: Discontinuity, compare people/units very close to the discontinuity with each other
How it works

- Discontinuity as core element (Angrist/Pischke, Figure 6.1.1)
How it works

• Assignment variable X: Treatment is assigned to individuals with a value of X greater or equal to a cutoff value c (cutoff=threshold)

• However, the discontinuity is not sufficient to justify the validity of an RD design

• If individuals – even while having some influence – are unable to precisely manipulate the assignment variable, a consequence of this is that the variation in treatment near the threshold is randomized as though from a randomized experiment

• This is a crucial feature of the RD design
How it works

• Intuitively, when individuals have imprecise control over the assignment variable, even if some are especially likely to have values of X near the cutoff, every individual will have approximately the same probability of having an X that is just above (receiving the treatment) or just below (being denied the treatment) the cutoff – similar to a coin-flip experiment
RD versus IV

• This result clearly differentiates the RD and IV approaches

• IV: one must assume the instrument is exogenously generated as if by a coin flip (which is difficult to justify)

• By contrast: RD design mimics a coin-flip randomization as a consequence of the assumption that individuals have imprecise control over the assignment variable
RD designs as local randomized experiment

- RD designs can be analyzed and tested
- If variation in the treatment near the threshold is approximately randomized, then it follows that all "baseline characteristics" – all those variables determined prior to the realization of the assignment variable – should have the same distribution just above and just below the cutoff. Thus, the baseline characteristics are used to test the validity of the RD design
Sharp RD design

Sharp RD is used when treatment status is a deterministic and discontinuous function of a covariate $x_i$ (Angrist/Pischke, 6.1.1 and 6.1.2)

$$D_i = \begin{cases} 
1 & \text{if } x_i \geq x_0 \\
0 & \text{if } x_i < x_0 
\end{cases}$$

$$E[Y_{0i}|x_i] = \alpha + \beta x_i$$

$$Y_{1i} = Y_{0i} + \rho$$

Estimation: $$Y_i = \alpha + \beta x_i + \rho D_i + \eta_i$$

Rho can be interpreted as causal effect
Non-linear case

Non-linear case: Adding polynomials

Check validity of nonparametric estimation strategy

- Is it really a jump or just a mistaken for discontinuity (Panel C)

- If yes, then e.g. Weighted Least Square (WLS) which weights points closer to the cutoff more

- If yes, check pretreatment variables near the discontinuity (are there significant differences? They should not be like with randomization)
Example: Lalive 2007

Extended benefit duration: Effect on unemployment duration
Austrian unemployment insurance system
209 week longer (case 1) or 39 weeks longer (case 2)
Discontinuity at threshold = 14.798; with std. err. = 1.928.

**Figure 1. The Effect of 170 Weeks of Extended Benefits for Men**
Discontinuity at threshold = 109.645; with std. err. = 4.927.

**Figure 2. The Effect of 170 Weeks of Extended Benefits for Women**
Example: Lalive 2007

### Table 1—The Effects of Extended Benefits on Labor Market Outcomes

<table>
<thead>
<tr>
<th>Benefits extended by (weeks)</th>
<th>Sample</th>
<th>170</th>
<th>170</th>
<th>13</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Men</td>
<td>Women</td>
<td>Men</td>
<td>Women</td>
</tr>
<tr>
<td>A. Unemployment duration (weeks)</td>
<td></td>
<td>14.798</td>
<td>109.645</td>
<td>−0.326</td>
<td>6.067</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.717)***</td>
<td>(6.088)***</td>
<td>(0.973)</td>
<td>(2.314)**</td>
</tr>
<tr>
<td>B. Fraction leaving for job</td>
<td></td>
<td>−0.044</td>
<td>−0.526</td>
<td>−0.011</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)***</td>
<td>(0.041)***</td>
<td>(0.007)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>C. Duration until exit to job (weeks)</td>
<td></td>
<td>1.542</td>
<td>2.924</td>
<td>−0.585</td>
<td>2.935</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.471)***</td>
<td>(1.087)**</td>
<td>(0.392)</td>
<td>(0.811)***</td>
</tr>
<tr>
<td>D. Change in log earnings</td>
<td></td>
<td>−0.000</td>
<td>0.010</td>
<td>−0.001</td>
<td>−0.020</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Number of spells</td>
<td></td>
<td>9.734</td>
<td>5.659</td>
<td>17.572</td>
<td>7.063</td>
</tr>
</tbody>
</table>

*Notes:* Each row contains estimated effect of extended benefits. Age-cell cluster robust standard errors are in parentheses. *Source:* Own calculations, based on Austrian Social Security data.
Identification and Interpretation

RD design is a local randomized experiment

i.e. If individuals have imprecise control over the assignment variable, then the treatment is „as good as“ randomly assigned around the cutoff (Lee/Lemieux, p. 16)

Comparison with gold standard social experiment
Figure 3: Randomized Experiment as a RD Design

- \( E[Y(1)|X] \)
- \( E[Y(0)|X] \)
- Observed (control)
- Observed (treatment)

Outcome variable (Y) vs. Forcing variable (random number, X)
Q1: When are the RDD identification assumptions plausible?

Answer according to Lee/Lemieux 2009: „When optimizing agents do not have precise control over the assignment variable – then the variation in the treatment will be as good as randomized in a neighborhood around the discontinuity threshold.“

Example for Nonappropriateness (p. 13)

Only precise sorting is self-selection

Some influence on the assignment variable is not a problem
Q2: Is there any way I can test those assumptions?

Yes. As in a randomized experiment, the distribution of observed baseline covariates should not change discontinuously at the threshold.
Q3: To what extent are results from RD designs generalizable?

The RD estimand can be interpreted as a Weighted average treatment effect across *all individuals*

Application: Incumbency paper in the tutorial
Tutorial

Sharp RD

Effect of party incumbency on reelection probabilities in the U.S. (Lee 2008)
Fuzzy RD = IV

Example: Angrist/Lavy 1999 Maimonides Rule
See Angrist/Pischke 2008 (pp. 263) for a summary
2SLS as estimation strategy
Causal effect is a LATE for compliers like IV