A Few More Clarifications

- What does "reduced form" mean?
- We previously talked about regressing treatment *X* on instrument *Z*, computing the fitted values of *X*, then regressing outcome *Y* on these fitted values.
    - The reduced-form equation "reduces" these two equations to a single equation, the regression of *Y* on *Z*.
    - The initials in the example's names (Alvaro, Camila, and Normando) correspond to always-takers, compliers, and never-takers.

A Few More Clarifications (cont.)

- The authors' Passover analogy is not entirely clear, but may be as follows for four types of children:
    - Wise (Compliers)
    - Wicked (Defiers)
    - Simple (Always-takers)
    - Doesn't know how to ask (Never-takers)
- "External validity" is a common term in academic social science, but I prefer the term "generalizability."

Vietnam Draft Lottery and Returns to Schooling

- IV can be used for natural experiments where the treatment is a continuous variable rather than binary.
- Angrist and Krueger (1992) used the Vietnam draft lottery as a natural experiment to assess returns to schooling on earnings.
  - During the Vietnam War, a fraction of young men from every birth year were prioritized for draft via a lottery system based on birth date.
  - Men with lower draft numbers became more likely to enroll in college, because an education deferment would allow them to avoid service.
  - Thus, the lottery created a random variation in the number of years of schooling, which created an opportunity to estimate returns to schooling.

Vietnam Draft Lottery and Returns to Schooling (cont.)

- We start the IV regression with a person's years of schooling *X* regressed on instrument *Z*, the order his birth date was pulled in the lottery.
  - Then we regress earnings Y on the predicted values of years of schooling *X*.
  - This tells us how the "clean" variation in number of years of schooling affects earnings.
- This IV regression is much better than simply regressing wages on years of schooling, which is fraught with OVB problems.

Potential Problem: Violation of the Exclusion Restriction

- The required assumption is that the random process cannot affect the outcome in any way other than the treatment being examined.
  - This assumption is no problem in many examples, such as the KIPP lottery.
- However, serving in Vietnam may affect earnings in ways unrelated to schooling. (E.g., if PTSD reduces earnings, we would underestimate returns to schooling.)
  - PTSD, for example, may reduce earnings. In that case, we would underestimate the returns to schooling.
- In the next example, David Broockman will describe a natural experiment where the exclusion restriction might be violated.

Does Economic Stagnation Cause War?

- Can foreign aid prevent civil war?
- Need randomly assigned economic growth.
  - Rain.
  - Rain tends to be associated with economic growth in agricultural areas.
- Compare countries with high rainfall to low.
- "If there's a correlation between rain and civil war, it could only be caused by lower economic growth."
- Policy recommendation: If war looks likely, send money.

Benefits of Natural Experiments

- If you are lucky enough to find one, you save the time of running the experiment yourself.
- Estimation is straightforward.
  - IV/2SLS is a very similar to OLS.
  - Estimation packages like "ivreg" in R give correct standard errors.

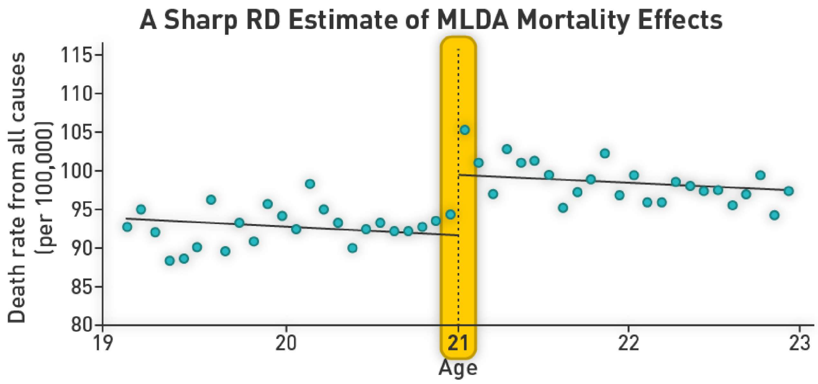
Disadvantages of Natural Experiments

- The actual administration of randomizing can be hard: People select, randomization fails, and so on.
  - In an observational natural experiment, you have no control over the design, data collection, execution, blocking, or attrition.
- You might not find a natural experiment on the topic you care about.
  - Good natural experiments can be as rare as unicorns, so we often have to run the experiments ourselves.

Reading

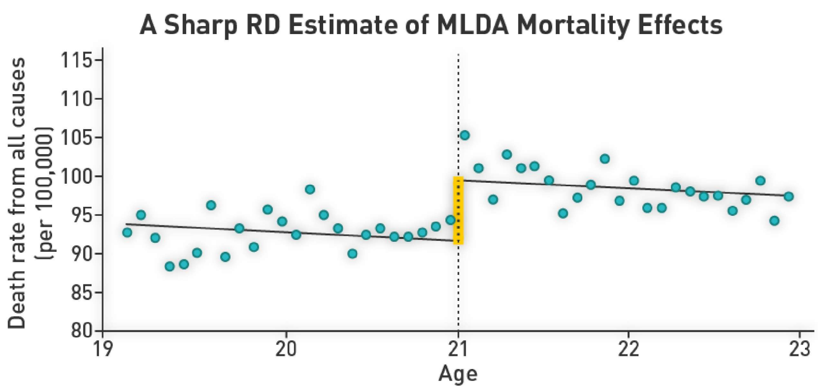
- Read *Mastering Metrics*, Section 4.1, pages 147–153, on measuring the mortality effects of drinking alcohol.
- Pay particular attention to Figure 4.2. How convincing is this as a demonstration of causal effect?

Regression Discontinuity: Figure 4.2



- There is a non-random "running variable": age.
- There is a "threshold": the minimum legal drinking age of 21.

Regression Discontinuity: Figure 4.2 (cont.)

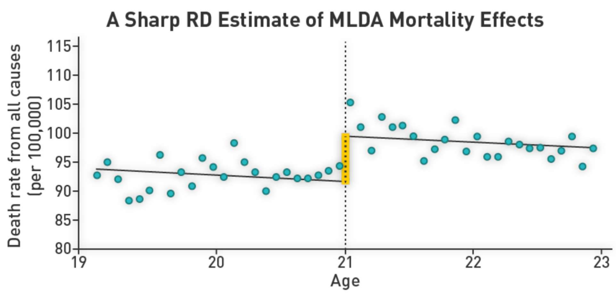


- It seems reasonable to believe that other reasons for mortality are exactly the same for someone who is 20 years, 364 days old, and someone who is exactly 21 years old.
  - If we compare people on either side of the discontinuity, the difference should be due only to the access to alcohol.

Equation 4.2

$$\bar{M}_a = \alpha + \rho D_a + \gamma a + e_a$$

- We regress the outcome (mortality rate) on:
  - A treatment dummy variable (are you over 21?)
  - A linear term for age, in years. The linear term allows for a time trend in mortality.



- Figure 4.2 shows the resulting regression line.
  - It is downward-sloping, except for a discrete jump on the 21st birthday.

Equation 4.2 (cont.)

- For a "fancy" analysis, we can use a quadratic regression (rather than linear), or we can allow the regression to change slope right at the discontinuity, but these are niceties.
  - We care most about the discrete jump in *Y* at the age discontinuity.

Reading

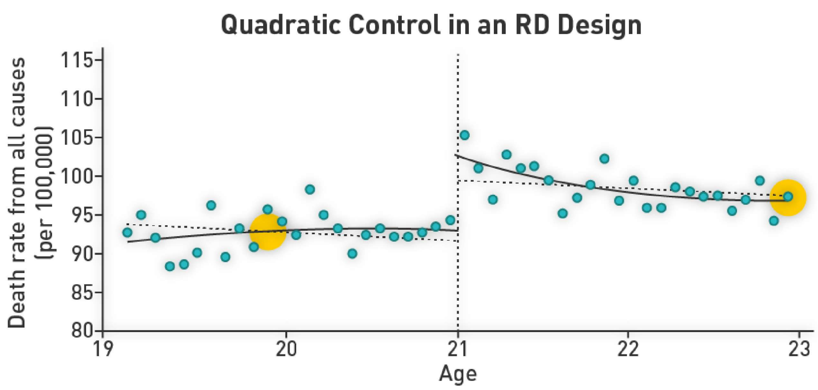
- Read *Mastering Metrics* from page 153 to the end of Section 4.1 on page 164.
- See if you can recognize the placebo tests.

Equation 4.4

$$\bar{M}_a = \alpha + \rho D_a + \gamma_1(a - a_0) + \gamma_2(a - a_0)^2 + \delta_1[(a - a_0)D_a] + \delta_2\left[(a - a_0)^2 D_a\right] + e_a$$

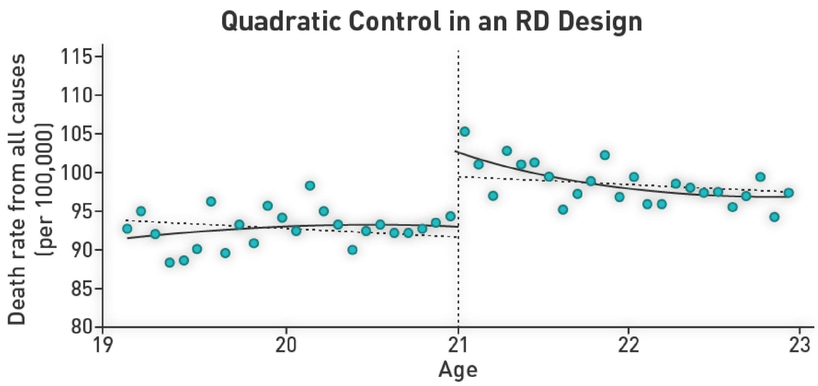
- This "fancy" regression allows the relationship between mortality and age to have one quadratic shape to the right of the 21st birthday and a different quadratic shape to the left.

Equation 4.4 Results: Figure 4.4



- The solid, curved line shows the fancy (quadratic) regression curve, while the dashed straight line shows the simple regression curve.
    - The slope of the simple curve must be the same on either side of the discontinuity.
    - The fancy curve has a different slope and curvature on each side.
        - This particularly captures the jump in mortality rates right after the 21st birthday.
        - The curve declines over time, but the mortality rate at age 23 is still a little higher than at 20.

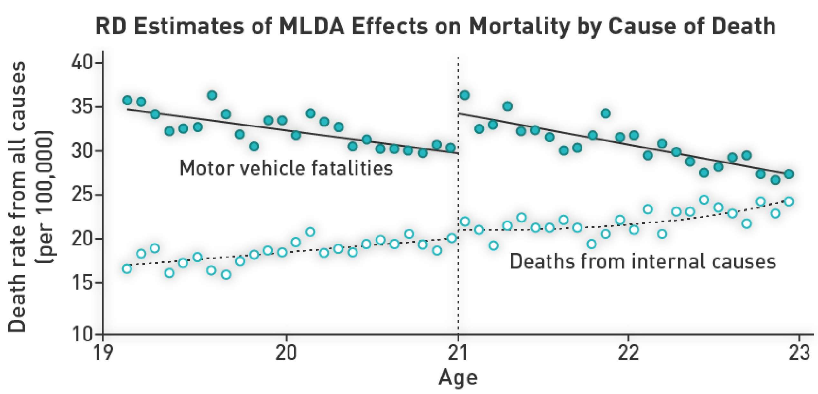
Equation 4.4 Results: Figure 4.4 (cont.)



- We don't want to extrapolate too far, as the power of an RD is right at the break point. But since the trends are gradual, some extrapolation may be OK.
  - Legal access to alcohol appears to produce higher mortality rates—especially at first, but potentially continuing for a couple of years before mortality rates return to baseline.

Placebo Tests: Figure 4.5

- Table 4.1 and Figure 4.5 show placebo tests.



- Deaths from disease ("internal causes") show no serious jump at the discontinuity, while motor vehicle fatalities show a substantial jump.
- This makes us even more confident that the jump we saw in the initial RD is really a causal effect of legal access to alcohol.
  - Deaths associated with alcohol show a big jump, while other causes of death don't seem to move.

Parametric vs. Nonparametric RD

- What we've seen in the earlier figures is **parametric RD:** we estimate regression lines or curves, and have a shift due to the treatment dummy variable.
- With **nonparametric RD**, we avoid assuming some parametric form, in case that might introduce specification error. Instead, we just look at the simple change in Y in a narrow window around the threshold.
- **Bandwidth** is the width of this window.

Parametric vs. Nonparametric RD: Table 4.1

Sharp RD Estimates of MLDA Effects on Mortality

Dependent variable	Ages 19–22		Ages 20–21	
	(1)	(2)	(3)	(4)
All deaths	7.66 (1.51)	9.55 (1.83)	9.75 (2.06)	9.61 (2.29)
Motor vehicle accidents	4.53 (.72)	4.66 (1.09)	4.76 (1.08)	5.89 (1.33)
Suicide	1.79 (.50)	1.81 (.78)	1.72 (.73)	1.30 (1.14)
Homicide	.10 (.45)	.20 (.50)	.16 (.59)	-.45 (.93)
Other external causes	.84 (.42)	1.80 (.56)	1.41 (.59)	1.63 (.75)
All internal causes	.39 (.54)	1.07 (.80)	1.69 (.74)	1.25 (1.01)
Alcohol-related causes	.44 (.21)	.80 (.32)	.74 (.33)	1.03 (.41)
Controls	age	age, age^2, interacted with over-21	age	age, age^2, interacted with over-21
Sample size	48	48	24	24

- In Table 4.1, the results are not very sensitive to the choice of window.
  - We see similar estimates when we compare Column 1 (window ages 19–22) to Column 3 (window ages 20–21).

Parametric vs. Nonparametric RD: Table 4.1 (cont.)

Sharp RD Estimates of MLDA Effects on Mortality

Dependent variable	Ages 19–22		Ages 20–21	
	(1)	(2)	(3)	(4)
All deaths	7.66 (1.51)	9.55 (1.83)	9.75 (2.06)	9.61 (2.29)
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Alcohol-related causes	.44 (.21)	.80 (.32)	.74 (.33)	1.03 (.41)
Controls	age	age, age^2, interacted with over-21	age	age, age^2, interacted with over-21
Sample size	48	48	24	24

- Trade-off:
  - Narrow bandwidth gives a much cleaner RD. We think all other things are equal on both sides of the threshold.
  - However, narrow bandwidth also cuts down the amount of data we can use, which decreases precision. Notice how Column 3 of Table 4.1 has larger standard errors than Column 1 does.

Policy Question

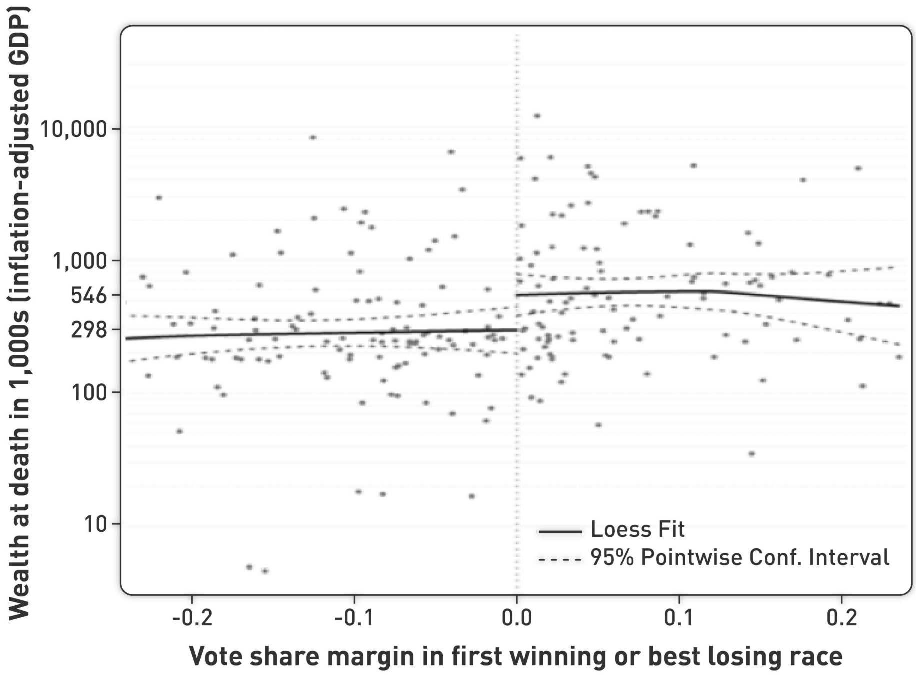
- Chapter 4 opened with the policy question, "What should the drinking
age be?"
- With RD, we saw that legal access to alcohol has a big causal effect on mortality for 21-year-olds.
- Does that tell us what would happen if we reduced the drinking age to 18?
    - Maybe, but we have to think about generalizability.

Policy Question (cont.)

- Earlier, we discussed "local average treatment effects." With RD, we get a very local ATE.
    - We have learned the effects of alcohol access on mortality for 21-year-olds, but we cannot be certain these results would generalize to 18-year-olds.
- Next, David Broockman will discuss a few more examples of RD.

Example of Regression Discontinuity

- Do unemployment benefits lead people to slack off?
- Ideal experiment: randomly assign some countries to strict unemployment regimes
- Find "naturally" occurring coin flip situations
- "Discontinuity" in Austria
  - People over 50 eligible for unemployment benefits
  - People under 50 not eligible
  - Does the age threshold affect worker productivity?
  - Simply comparing young vs. old could lead to false conclusion that being old causes difference in unemployment duration



Another Example

- Do people get rich by being elected?
- Ideal experiment: randomly assign person to be elected and measure his/her wealth upon death
- Eggers and Hainmueller
  - Examined wealth at death of British MPs who won or lost by narrow margins
- Interpretation issue: Are results simply due to MPs moving to London?

Common Issues With Regression Discontinuity Designs

"Sorting" at cut point

- Ex ante: "before the event"
    - People aware of threshold and can try to get above it
    - E.g., Latin honors
        - Effect of honors on success in labor market
        - Awareness of threshold results in better students just above cutoff
- Ex post: "after the event"
    - E.g., elections of Black mayors in 1970s
    - Black candidates disproportionately lost by slim margins
    - Manipulations make analysis difficult

Tests for Sorting

- Covariate balance on either side of cut point
    - Does covariate balance hold up based on early measurements?
- Smoothness (McCrary test)
    - E.g., effects of minimum-wage laws on unemployment
    - Comparison between states based on margin of vote passing
- Can't directly compare bills due to differences in the kinds of bills that just pass and just fail
- Check for proportion of observations in running variable
    - E.g., fraction of yes votes vs. treatment variable
- Passage of regression discontinuity check doesn't guarantee assumptions hold
- Check for lack of covariate balance, lack of smoothness

Reading Assignment

- The third observational technique we will consider is called "difference in differences" (DID).
- This technique is used when a natural experiment takes place over time, in a before-after setting, and when we don't have a randomized control group.
  - Instead, we have a group that is similar to the treated group but not guaranteed to be identical.
- Read *Mastering Metrics*, Section 5.1, page 178 through the top of page 187.

Note: Lecturer meant to say "...section 5.1."

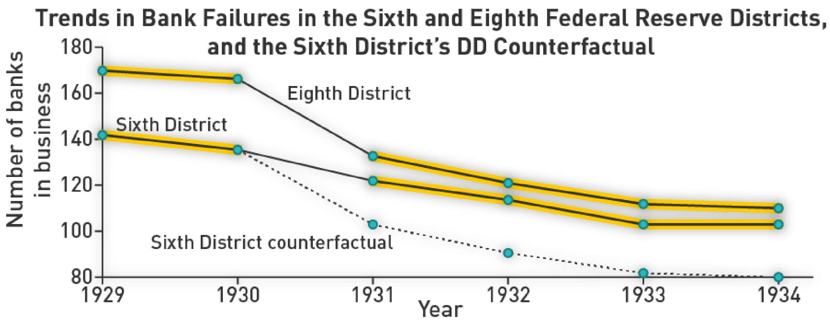
DID: Effects of Federal Reserve Lending Policy to Mississippi Banks

- It is difficult to do a field experiment on monetary policy.
- Instead, we look for a natural experiment.
    - In 1930, the Federal Reserve Bank of Atlanta (Sixth District) chose to provide much more credit to troubled banks than did the St. Louis Fed (Eighth District).
    - The state of Mississippi was divided almost equally between the
      two districts.

DID: Effects of Federal Reserve Lending Policy to Mississippi Banks (cont.)

- The banks are not randomized, so a simple difference can be misleading.
    - In 1931, 11 fewer banks were open in the Sixth District than in the Eighth, so we might be tempted to conclude that easy lending caused more banks to close.
        - But in 1930, before the crisis, 30 fewer banks were open in the Sixth District than in the Eighth.
    - We need to account for this baseline difference.
        - This is what DID does, by subtracting the before-after difference in the treatment group from the before-after difference in the pseudo-control group.

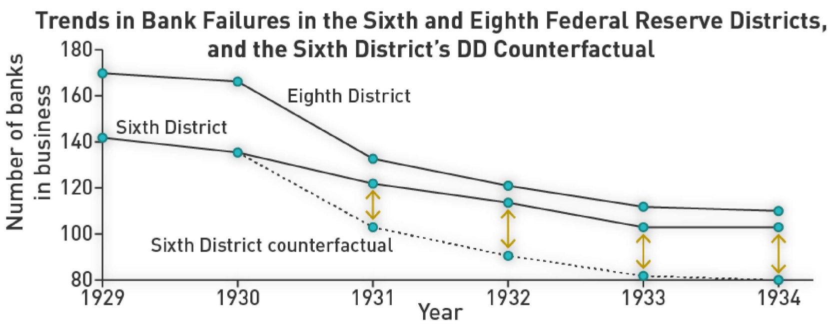
Figure 5.3: DID Strategy Illustration



Notes: This figure adds DD counterfactual outcomes to the banking data plotted in Figure 5.2. The dashed line depicts the counterfactual evolution of the number of banks in the Sixth District if the same number of banks had failed in that district after 1930 as did in the Eighth.

- To get a valid causal inference with DID, we need to satisfy the "**common trends**" (or "parallel trends") assumption.
- Figure 5.3 shows that this assumption is reasonable.
  - The hypothesized policy difference occurs in 1930.
  - In other years, the two lines (number of banks open) move in parallel.

Figure 5.3: DID Strategy Illustration (cont.)



Notes: This figure adds DD counterfactual outcomes to the banking data plotted in Figure 5.2. The dashed line depicts the counterfactual evolution of the number of banks in the Sixth District if the same number of banks had failed in that district after 1930 as did in the Eighth.

- The dashed line shows the counterfactual number of banks that would have been open in the Sixth District if the Atlanta Fed had not pursued an easy lending policy in 1930.
  - The difference between the Sixth District actual and hypothetical curves shows the estimated causal effect of the Sixth district's lending policy.

Reading

- Read the rest of *Mastering Metrics*, Section 5.1, pages 187–191, which discusses how to implement a DID strategy using regression.
- The technique will look familiar, if you remember the material on using regression to analyze heterogeneous treatment effects.

DID Regressions

- If we have more than two time periods or more than two comparison groups available, we can implement DID via a regression.

$$Y_{dt} = 167 \underset{(8.8)}{- 29} TREAT_d \underset{(7.6)}{- 49} POST_t \underset{(10.7)}{+20.5}(TREAT_d \times POST_t) + e_{dt}$$

- **TREAT** is a dummy variable equal to one in the treatment group (here, the
Sixth District).
  - The coefficient of −29 means that in the pretreatment baseline period, there were 29 fewer banks open in the Sixth District than in the Eighth.

DID Regressions (cont.)

$$Y_{dt} = 167 \underset{(8.8)}{- 29} TREAT_d \underset{(7.6)}{- 49} POST_t \underset{(10.7)}{+20.5}(TREAT_d \times POST_t) + e_{dt}$$

- **POST** is a dummy variable equal to one during the treatment time period, zero before the period.
  - The coefficient of −49 means there was a downward trend in banks open before and after 1930 (49 fewer banks on average during the postperiod than in the preperiod in the Eighth District).
- The coefficient of 20.5 on the interaction term is the estimated causal effect of easy lending policy to troubled banks.
  - I.e., the difference in the postperiod vs. the preperiod in the treatment group, relative to the difference in the comparison group
- Next, David Broockman will share some additional examples of DID.

Ladd and Lenz (2009)

- Does the media affect political outcomes?
    - Specifically newspaper endorsements
- Ideal experiment: Randomly assign newspapers to endorse a candidate.
- People often read newspapers that reinforce their views.
    - Do readers' views change if newspaper switches endorsement?
- Data on voters' decision to vote for Labour Party in 1992 and '97.
    - Which newspapers voters read.
    - Some newspapers switched endorsement to Labour Party.
- Key assumption: nothing changing over time that leads to treatment and outcome.
    - Consider other reasons for results.

Potential Problems with Ladd and Lenz (2009)

- Big housing crisis in 1997.
    - People voted for Labour due to frustrations with incumbents.
- People with homes more upset over housing crisis.
- People with homes more likely to get newspapers.
    - Homeowners more likely to receive treatment, vote based on housing crisis.
- Placebo test.
    - DiD when treatment didn't change.
    - No effect seen among readers of other papers.

How Does Advertising Prices Change Level of Prices?

- Rhode Island banned advertising prices of alcohol.
    - Will firms offer less competitive pricing as a result?
- Could compare Rhode Island alcohol prices to those in Connecticut and Massachusetts.
    - Other conditions between states might differ.
- Rhode Island ended advertising ban.
    - Can't simply do a before/after analysis
    - Price change could reflect other factors.

Rhode Island and Massachusetts

- Compare changes in Rhode Island to changes in Massachusetts.
    - Prices increased 2% in Rhode Island.
    - Likely due to inflation
- Milyo and Waldfogel (1999) collected data on liquor prices in RI and MA, before and after advertising ban.
    - Had foresight to collect data when Supreme Court agreed to hear case on advertising ban.
    - Found prices in RI **decreased** relative to same goods in MA.
    - Prices didn't drop for products that were never advertised.
    - Prices dropped only for advertised products.

Review of Differences-in-Differences

- DiD helps counteract selection effects.
- Can't always directly compare two entities.
- Before/after effects can be misleading.

Home Prices and Incinerator Location

- How much do property values drop as a result of having incinerator nearby?
- Can't simply look at home prices in relation to distance from incinerator.
    - Have to ask why some places have incinerators while others don't.
    - Ideal experiment: Randomly assign location of incinerators.
    - Incinerators tend to be built in bad neighborhoods.
        - Property values are inherently lower to begin with.
    - Unobserved heterogeneity.
        - E.g., bad construction, recently built development

Kiel and McClain (1995)

- DiD approach
- Collected data in two time periods
    - Before incinerator was announced and after it was built
- Compared data in North Andover to other locations
- Found home prices near incinerator increase about 5% less; not statistically significant
    - Other characteristics matter more.
    - Extra bathroom: +13% +/− 5%
    - Average prices over time (before/after): +14% +/− 6%

Importance of the DiD Approach

- Home prices near incinerator could have had lower baseline.
  - Result of preexisting differences
- Protects from false conclusions drawn from simple before/after approach.
- Vulnerabilities still exist.
  - E.g., demographic changes could lead to incinerator being built in the first place.

Strengths of DID

- DID is a simple tool: We compute differences directly, or do OLS regression with clustered standard errors.
- If we have covariates that might predict differences in Y, we can include them to try to improve precision.
- Causal effects are much more believable than with simple before-after differences or simple differences across (nonrandomized) comparison groups.

Weaknesses of DID

- Causal inference hinges on the assignment mechanism.
- The common trends (parallel trends) assumption is a strong assumption. Consider the observational.
- Consider the observational online-advertising example:
  - People may be gone on vacation.
  - People may see simultaneous newspaper advertising campaigns.