ECON 8000/9000 Empirical Energy Econ

Topic 05: Review of RD Design

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February 2, 2026

Outline

- Review: RD Regressions
- Example RD Englmaier et al. (2024) Mgm Science
- Example RDiT Smith (2017) AEJ:AE

Review RD

Let's review the 101

Typical terminologies:

- Running variable
- Cutoff
- Treatment
- Bandwidth selection

Typical methodologies:

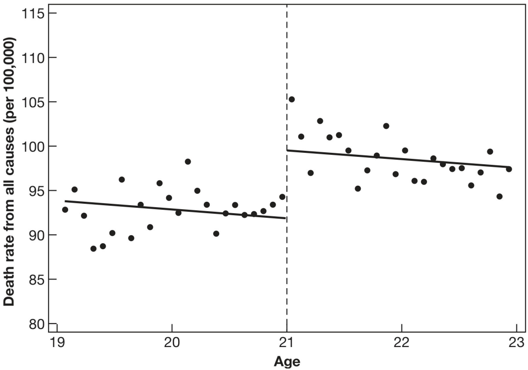
- Sharp RD
- Fuzzy RD
- RDD vs. RKD
- RD in Time (RDiT)

1.1 RDD: Sharp RD

Minimum Legal Drinking Age (MLDA) by Carpenter & Dobkin (2009) AEJ:AE

- A simple setup: $y_i = \beta_0 + \beta_1 \mathbf{1}\{age_i \geq 21\} + \beta_2 age_i + \varepsilon$
- Running variable: age
- Treatment is determined by $\mathbf{1}\{age \geq 21\}$: There is exogenous variation

A sharp RD estimate of MLDA mortality effects



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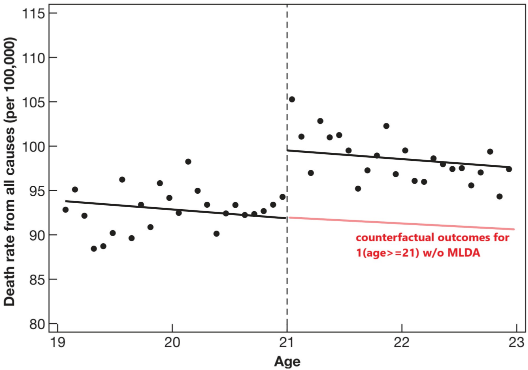

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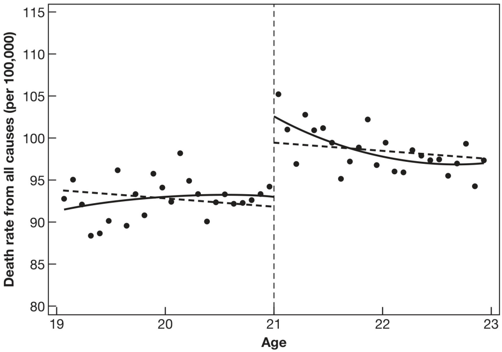
FIGURE 4.4
Quadratic control in an RD design



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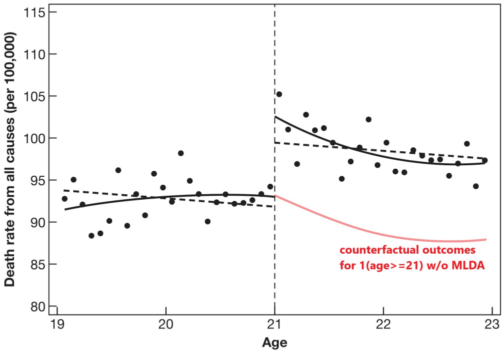
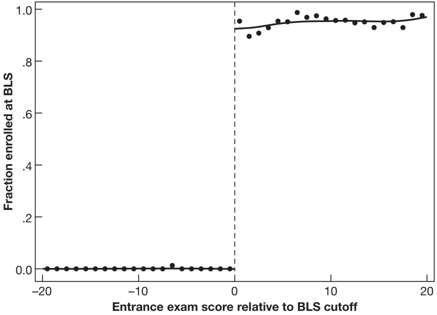


1.2 RDD: Fuzzy RD

Entrance Exam Score and Enrollment by Angrist & Rokkanen (2015) JASA

- Run this as a sharp RD: $enrollment_i = \beta_0 + \beta_1 \mathbf{1}\{score_i \geq cutoff\} + \beta_2 score_i + \varepsilon$
- Running variable: entrance exam score
- In what scenario should we consider fuzzy RD?
  Hint: Is treatment strictly determined by $1\{\text{score}_i \geq cutoff\}$?

Enrollment at BLS



Notes: This figure plots enrollment rates at Boston Latin School (BLS), conditional on admissions test scores, for BLS applicants scoring near the BLS admissions cutoff. Solid lines show fitted values from a local linear regression

1.2 RDD: Fuzzy RD

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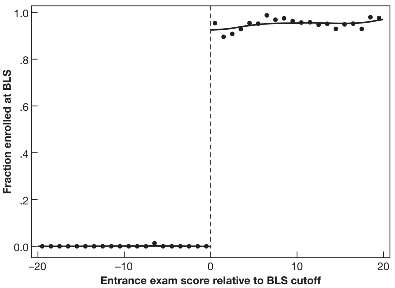
- Run this as a sharp RD: $enrollment_i = \beta_0 + \beta_1 \mathbf{1}\{score_i \geq cutoff\} + \beta_2 score_i + \varepsilon \cdots (1)$
- Consider an unobserved latent cutoff that only admission officers know, denoted as *Rcutoff*
- Treatment: passing the latent cutoff $\mathbf{1}\{score_i \geq Rcutoff\}$

Enrollment at BLS



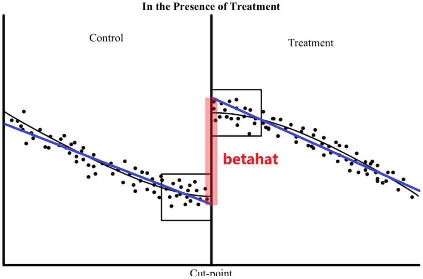
Notes: This figure plots enrollment rates at Boston Latin School (BLS), conditional on admissions test scores, for BLS applicants scoring near the BLS admissions cutoff. Solid lines show fitted values from a local linear regression

- Then what is $\mathbf{1}\{score_i \geq cutoff\}$ in Eq(1)?
- You can think of it as an IV for the unobserved treatment
- So the above equation is the reduced-form version of an IV regression
- Just like IV, local identification

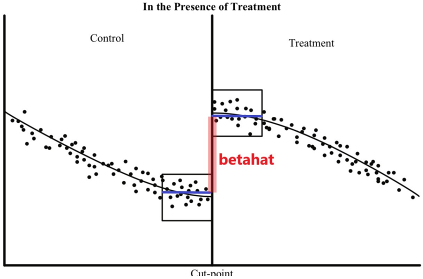
1.2 RDD: Fuzzy RD

Bandwidth selection

- Imagine we just fit $y = \beta_0 + \beta_1 \mathbf{1}\{x \geq \bar{x}\} + \beta_2 x + \varepsilon$, aka y on cutoff dummy + running var x
- In this example, we will overestimate the actual RD effect given the curvature
- The RD effect can be overestimated as well
- In practice, people do bandwidth selection, e.g., `rdrobust` in Stata, R, and Python



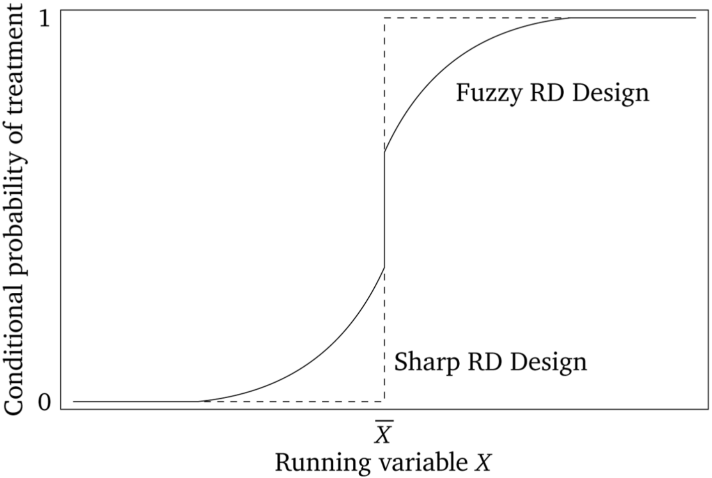
Without bandwidth selection



With bandwidth selection

1.3 Exogeneity Requirement around Cutoff

For both Sharp and Fuzzy RD



1.3 Exogeneity Requirement around Cutoff

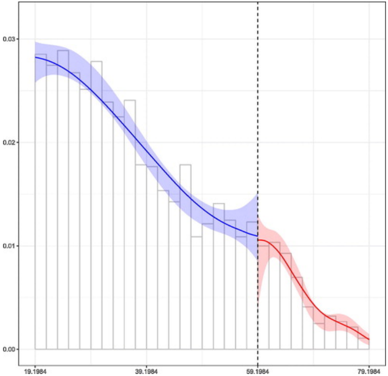
Checks/tests

- Just like IV, the exogeneity cannot be proved... and can only be argued
- But one can produce some helpful test
- Density test: `rddensity` in Stata, R, and Python
  - Test if the running variable has manipulation around the cutoff
  - This is known a **Manipulation Test**
  - Aka, look for **overlapping CI** around the cutoff
- Other usage for `rddensity` in settings
  - `rddensity` plots are used also in bunching
  - However, in the scenario studying bunching, usually people look for **non-overlapping CI**

Use rddenstiy as a Manipulation Test for RD

Passing the test requires: overlapping CIs

- Consider $y = \beta_0 + \beta_1 \mathbf{1}\{x \geq \bar{x}\} + \beta_2 x + \varepsilon$
- x is poverty index, $\bar{x} = 59.19$ is Head Start(HS) eligibility, and y is an outcome for HS
- Test there is no manipulation around the eligibility cutoff
- Run `rddensity` on the distribution for the running variable x



Source: Cattaneo, Jansson, and Ma (2020) JASA

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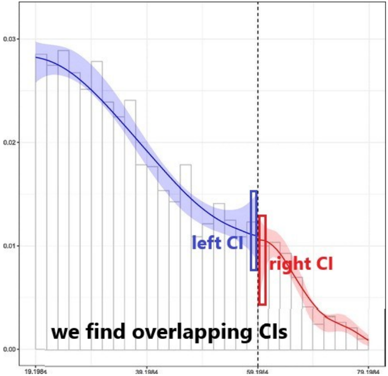

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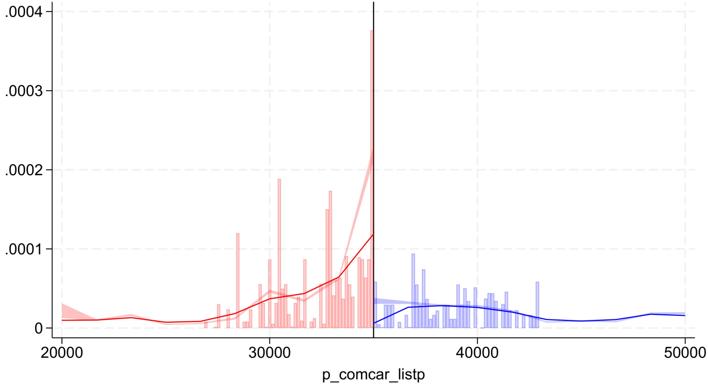
Use rddenstiy to Study Bunching Per Se

Evidence of Bunching requires: Non-overlapping CIs

- If the goal is to study a variable and see if there is bunching behavior
- Run rddensity on the bunching var: only non-overlapping CI suggests bunching
- In the UK after March 2021, EV subsidies eligibility dropped from below-50k to below-35k
- Here we study if and to what extent that carmakers list EVs below £35k after March 2021



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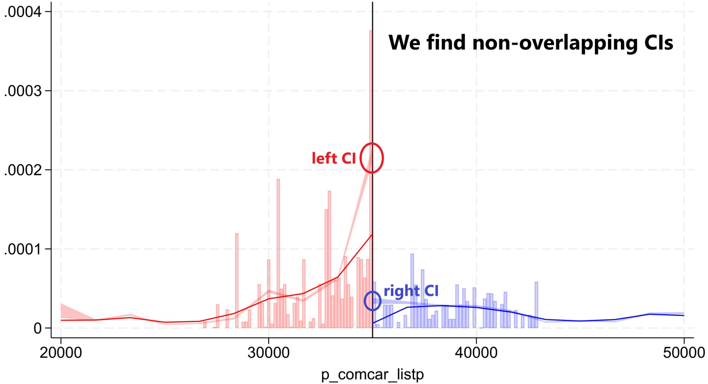
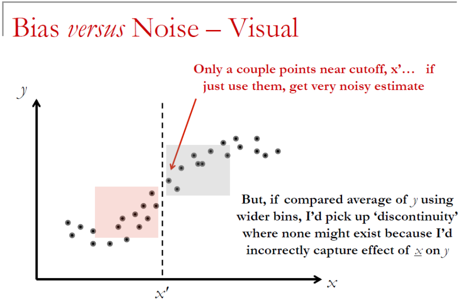
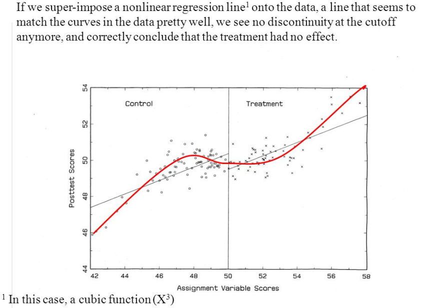


1.4 Fake RDs

The important thing is not to kid oneself when studying RD





2. RD in Time (RDiT)

Typical RD vs RDiT

Typical RD

- Use cross-sectional variation around the cutoff: exam score, poverty rate, other eligibility
- Assumption required
  - Within a time t, there needs to have cross-sectional exogeneity around the cutoff across units i
  - For units near the cutoff, they are as-good-as-random to be above or below cutoff
  - Aka, no manipulation, no sorting, etc around the cutoff

RDiT

- Running variable is time t
- Cutoff is a specific time, say $\bar{t}$
- Exogeneity variation needed: time-series variation
- Within each unit i, outcome $y_{it}^{\text{right before } \bar{t}}$ and $y_{it}^{\text{right after } \bar{t}}$ should be apple-to-apple comparison
- Within each unit i, there should be no anticipation or sorting
- There should be enough observation within each i near $\bar{t}$ as well

2. RD in Time (RDiT)

Challenges for RDiT

- See Rapson & Hausman (2018) Annual Review of Resource Economics "RDiT: Considerations for Empirical Applications"
- As all units will go through the time, we don't have as-good-as random around $\bar{t}$
- Ideal data structure
  - Need longer time, otherwise we cannot effectively use the running variable time t
  - High frequency data, daily or more frequent (weekly data may be ok)
  - Q1: Why do we need above?

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- Key challenge: insufficient variation around cutoff time $\bar{t}$
  - So SE may be way too large to identify the RD effect
  - Solution: increase bandwidth to solve this problem and to get a more precise estimate
  - Tradeoff for this solution: Within each unit i, behavior right before $\bar{t}$ and after $\bar{t}$ may be more likely to be subject to bias as we increase the "local window"

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- Other challenges
  - It is not obvious how we should deal with time-series correlation within the error term
  - It doesn't make much sense to run the `rddensity` manipulation test anymore
  - Q2: Why does `rddensity` become useless in most RDiT settings?
- The justification for identification usually relies on reliable arguments alone
  - E.g., non-anticipation and no-sorting

Outline

- Review: RD Regressions ✓
- Example RD Englmaier et al. (2024) Mgm Science
- Example RDiT Smith (2016) AEJ:AE

Outline

- Review: RD Regressions ✓
- Example RD Englmaier et al. (2024) Mgm Science (Done in Topic 4) ✓
- Example RDiT Smith (2016) AEJ:AE

Smith (2016) AEJ:AE

"Spring forward at your own risk: Daylight saving time and fatal vehicle crashes"

Research Question: What is the unintended consequence of Daylight Saving Time (DST) in terms of motor vehicle accidents?

DST

- Many countries have DST
- Typical format: Spring-forward and fall-back
- Historical justification for DST: shift energy consumption within a day for energy saving
  Historically, the majority % of evening energy consumption was lighting

Two key important types of variation used here:

- A RDiT variation x2 per year in the spring and the autumn (can use RD estimator)
- A 2005 DST policy shift (can use FE estimator)
  Before 2007: DST starts on 1st Sun of Apr, ends on last Sun of Oct
  Since 2007: DST starts on 2nd Sun of Mar, ends on 1st Sun of Nov

Studies on DST

DST was motivated by potential energy-saving benefit...

A few strands of studies on DST

- Q1. Does DST actually have any energy-saving benefits?
  If so, what are the mechanisms? Who benefits?
  If not, why? Through what mechanisms do benefits and costs cancel out, or worse?
- Q2. Does DST have any unintended consequences?
  Health issues? safety? economic impacts? agricultural? etc?

Smith (2016) AEJ:AE "DST and Crashes"

Key variation

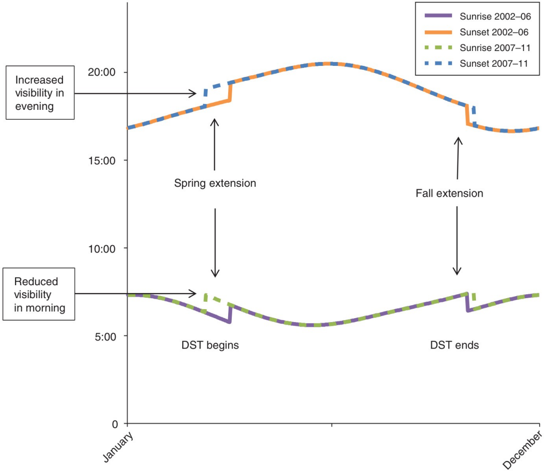

FIGURE 1. THE INFLUENCE OF DAYLIGHT SAVING TIME ON AMBIENT LIGHT

Note: The sunset and sunrise times are for St. Louis, Missouri, the nearest major city to the population center of the United States.

Smith (2016) AEJ:AE "DST and Crashes"

Suggestive evidence for the RDiT design for "spring-forward"

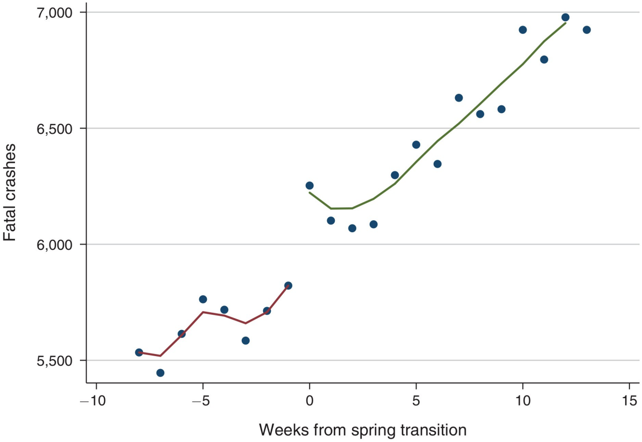

Figure 2. Fatal Crashes around the Spring Transition

Notes: Each point represents the total number of fatal crashes occurring during that week from 2002–2011. Smoothed lines are results of locally weighted regressions.

Smith (2016) AEJ:AE "DST and Crashes"

Key Data

- Main data: Fatality Analysis Reporting System (FARS) from NTHSA, 2002-2011
    - FARS documents individual crashes, as we discussed in Scott (2022)
    - Upside: Can organize the crash data into daily level
      $\Rightarrow$ The high-frequency nature makes RDiT feasible
    - Downside: Very sparse (by the nature of fatal crashes)
      $\Rightarrow$ Have to aggregate to national level
      Otherwise, not enough data points around cutoff time $\bar{t}$
      Ergo, cannot use locational FE such as state FE
- Data for additional outcome: Daily VMT from California
    - Performance Measurement System (PeMS) from CA
    - VMT from NHTS will not be helpful. Why?

Smith (2016) AEJ:AE "DST and Crashes"

Main estimation equations: 1. A RDiT design

For day d in year y, estimate Eq(1) with bandwidth selection using `rdrobust`:

$$\ln Fatals_{dy} = \beta_0 + \beta_1 DST_{dy} + f(DaysToTran_{dy}) + f(DST_{dy} \cdot DaysToTran_{dy}) + \varepsilon_{dy} \quad \text{(Eq(1) RD)}$$

- $\ln Fatals$: log daily fatal crash demeaned by (i) year and (ii) day-of-week
- $DaysToTrans$: running variable t relative to cutoff date
- DST: dummy variable that the running variable passes cutoff date
- β_1: main RD parameter of interest
- $f(\cdot)$: local linear function
- Q1: Why does the author need to demean yvar?

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Additional placebo test: Re-define cutoff date

- Assign placebo DST for 2002-2006 using the later DST for 2007-2011
- Assign placebo DST for 2007-2011 using the prior DST for 2002-2006

Smith (2016) AEJ:AE "DST and Crashes"

Main estimation equations: 2. A FE design

For day d in year y, estimate Eq(2):

$$\ln Fatals_{dy} = \beta_0 + \beta_1 SprgDST_{dy} + \beta_2 FallDST_{dy} + \phi_d + \phi_w + \phi_y + \varepsilon_{dy} \quad \text{(Eq(2) FE)}$$

- $\ln Fatals$: log daily fatal crash demeaned by (i) year and (ii) day-of-week
- $SprgDST$: 1 if dy is from the spring DST starting-date to 6/30
- $FallDST$: 1 if dy is from 7/1 to the fall DST ending-date
- β_1 and β_2: main RD parameter of interest
- FEs
  - ϕ_d: day of the year FEs
  - ϕ_w: day of the week FEs
  - ϕ_y: year FEs
- Q2: What data points are served as control/comparison group?

Before Main RDiT Results

Residual Plot

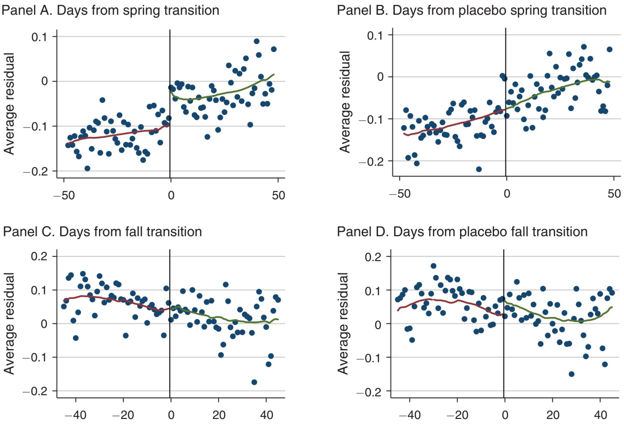

FIGURE 4. RESIDUAL PLOTS—SPRING, FALL, AND PLACEBO TRANSITIONS

Notes: The residuals are generated from a regression of ln(fatal crash count) on day-of-week and year dummies. Each point is the average of all residuals for that date relative to the true or placebo transition. Placebo is as defined in the text. Fitted lines are results of locally weighted regressions.

- Q3: Note the residuals here are not $\hat{\varepsilon}_{dy}$. Then what are they then?
- Q4: What is the purpose of this exercise?

Before Main RDiT Results

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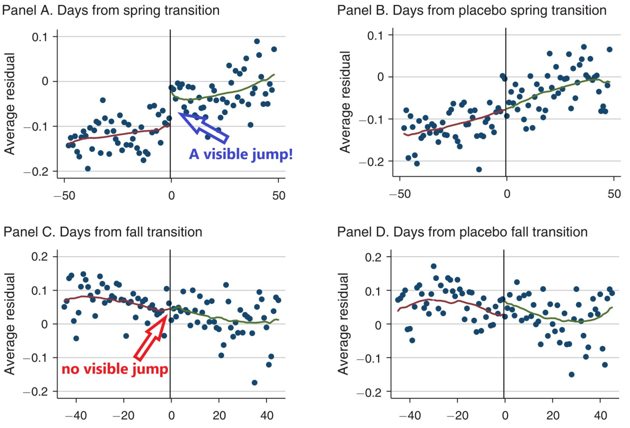

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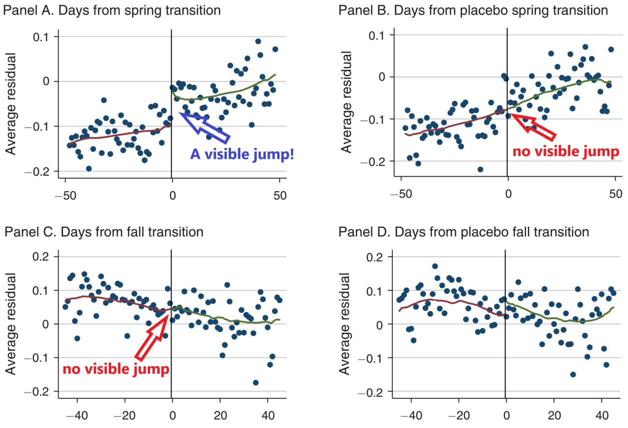

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Main RDiT Results

Spring DST Transition (a 6.5% rise in crashes) vs Fall DST Transition (null effect)

TABLE 1—RD ESTIMATES OF THE IMPACT OF ENTERING DST ON FATAL CRASHES *(Spring)*

	(1)	(2)	(3)	2002–2006 (4)	2007–2011 (5)	Placebo (6)
DST	0.0649***	0.0499***	0.0626***	0.0941***	0.0375	0.000536
	(0.0231)	(0.0176)	(0.0215)	(0.0302)	(0.0361)	(0.0225)
Bandwidth selector	CCT	IK	CV	CCT	CCT	CCT
Observations	550	966	670	235	265	550

TABLE 2—RD ESTIMATES OF THE IMPACT OF LEAVING DST ON FATAL CRASHES *(Fall)*

	(1)	(2)	(3)	2002–2006 (4)	2007–2011 (5)	Placebo (6)
Leaving DST	0.00114	−0.000182	0.00630	0.0274	−0.00260	0.0361*
	(0.0236)	(0.0153)	(0.0242)	(0.0265)	(0.0327)	(0.0218)
Bandwidth selector	CCT	IK	CV	CCT	CCT	CCT
Observations	381	850	347	215	225	381

- Note the small number of observations, very typical in RDiT

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More Placebos for the RDiT

Define cutoff dates in each day in calendar year (outside bandwidth), about 300 days

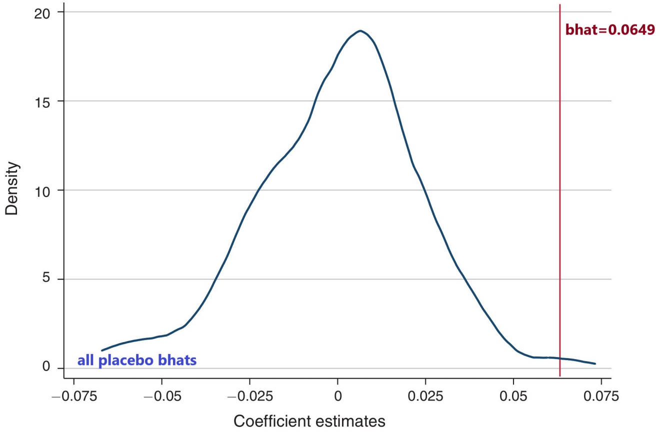

FIGURE 5. DISTRIBUTION OF COEFFICIENT ESTIMATES FROM PERMUTATION TEST

Notes: The kernel density function uses an Epanechnikov kernel and shows the distribution of coefficient estimates from the permutation test described in the text. The vertical line at 0.0649 is the true effect found for the spring transition. The *p*-value implied from this permutation test is 0.007.

Plan B for Manipulation Test

How to provide evidence to support for no-sorting?

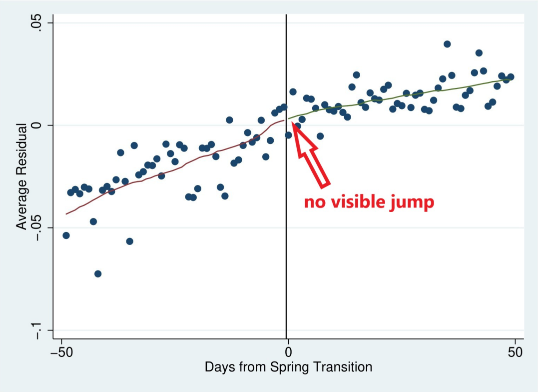

Figure B-3. : VMT Residual Plot

Note: Residuals from a regression of ln(VMT) on day-of-week and year dummies.

- We can no longer run the manipulation test `rddesntity` on running variable (time)
- But, we can re-run RD regression on other yvars that may suggest sorting
- What to look for: zero jumps in these vars
- In this example: Daily VMT from California

Mechanism discussion

Possibility 1: Ambient light?

TABLE 3—RD ESTIMATES OF THE INFLUENCE OF AMBIENT LIGHT ON FATAL CRASHES WHEN LEAVING DST (*Fall*)

	Morning			Evening			Least light impacted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Leaving DST	–0.115**	–0.180***	–0.128**	0.187***	0.147***	0.180***	–0.0134
	(0.0501)	(0.0386)	(0.0569)	(0.0457)	(0.0321)	(0.0380)	(0.0275)
Bandwidth selector	CCT	IK	CV	CCT	IK	CV	CCT
Observations	580	989	482	467	886	616	415

Table B-7—: Spring RD estimates by time of day (spring analog to Table 3)

	Morning			Evening			Least Light Impacted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Leaving DST	0.198***	0.188***	0.176***	-0.0335	-0.0197	-0.0430	0.0751**
	(0.0485)	(0.0423)	(0.0358)	(0.0388)	(0.0292)	(0.0374)	-0.0266
Bandwidth Selector	CCT	IK	CV	CCT	IK	CV	CCT
Observations	810	1,040	1,414	790	1,336	830	530

- The fall exercise indicates ambient lighting likely only causes a shift within a day
- The spring exercise indicates a slightly different story

Mechanism discussion

Possibility 2: Lack of sleep?

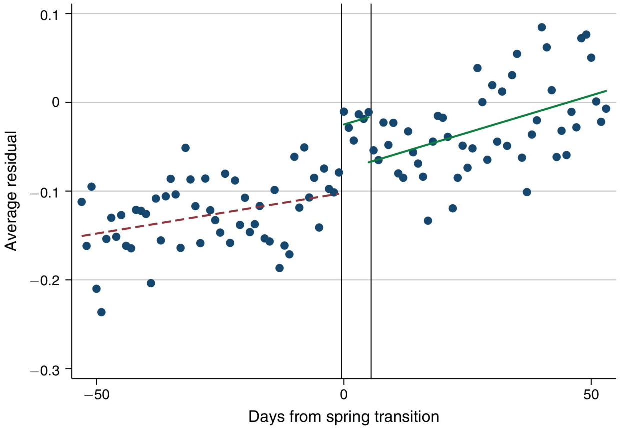

FIGURE 7. SPRING RESIDUAL PLOT—SIX-DAY SLEEP IMPACT

- This plot is somewhat weak
- We will see much stronger evidence next
- Q5: Why is this plot weak?
- Q6: Does the nature of RDiT have something to do with this?

Mechanism discussion

Possibility 2: Lack of sleep?

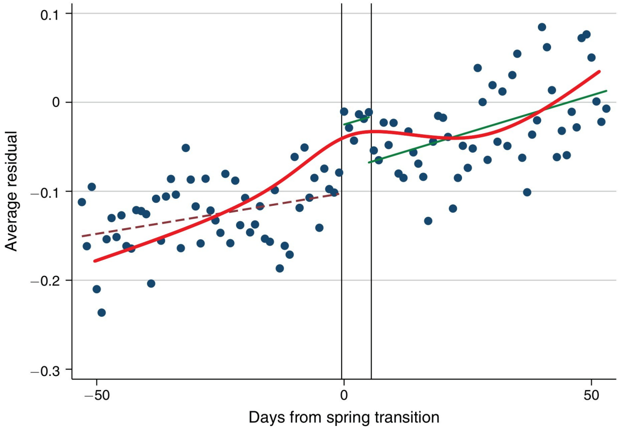

FIGURE 7. SPRING RESIDUAL PLOT—SIX-DAY SLEEP IMPACT

- This plot is somewhat weak
- We will see much stronger evidence next
- Q5: Why is this plot weak?
- Q6: Does the nature of RDiT have something to do with this?

Mechanism discussion

Possibility 2: Lack of sleep?

TABLE 4—RD ESTIMATES OF THE INFLUENCE OF SLEEP LOSS ON FATAL CRASHES (*Spring*)

	All hours	Least light impacted hours		
	(1)	(2)	(3)	(4)
DST	0.0649***	0.0751***	0.0540**	0.0683***
	(0.0231)	(0.0266)	(0.0219)	(0.0238)
Bandwidth selector	CCT	CCT	IK	CV
Observations	550	530	810	670

- Robust results across various hours, esp the least impacted hours
- Could be driven by lack of sleep, disruption in circadian rhythm, other biological factors that affect human saftey/performance of operating motor vehicles
- Much stronger evidence than Figure 7

FE Results

Again: Spring DST vs Fall DST

TABLE 5—FE ESTIMATES OF THE IMPACT OF DST ON FATAL CRASHES—DECOMPOSING SPRING DST

	All hours				Least light impacted	Morning	Evening
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Spring DST	0.0319*	0.0307*					
	(0.0165)	(0.0165)					
First six days of DST			0.0565**	0.0559**	0.0574**	0.205***	−0.0265
			(0.0231)	(0.0230)	(0.0272)	(0.0514)	(0.0453)
Next eight days of DST			0.0254	0.0240	0.0289	0.130**	−0.0812*
			(0.0201)	(0.0201)	(0.0234)	(0.0603)	(0.0450)
Remainder of spring DST			0.0142	0.0123	0.00907	0.126**	−0.0588
			(0.0197)	(0.0197)	(0.0230)	(0.0553)	(0.0429)
Fall DST	0.0228	0.0221	0.0218	0.0211	0.0446	0.259***	−0.159***
	(0.0249)	(0.0247)	(0.0250)	(0.0248)	(0.0303)	(0.0709)	(0.0482)
ln(gas price)		−0.0457*		−0.0469*	−0.0449	−0.101*	−0.0307
		(0.0246)		(0.0247)	(0.0289)	(0.0557)	(0.0484)
Observations	3,341	3,341	3,341	3,341	3,341	3,341	3,341
Adjusted R^2	0.734	0.735	0.735	0.735	0.753	0.184	0.319

FE Results

Spring DST's temporarily effect

TABLE 5—FE ESTIMATES OF THE IMPACT OF DST ON FATAL CRASHES—DECOMPOSING SPRING DST

	All hours				Least light impacted	Morning	Evening
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Adjusted R^2	0.734	0.735	0.735	0.735	0.753	0.184	0.319