STA 235H - Regression Discontinuity Design

Fall 2021

McCombs School of Business, UT Austin

Housekeeping

Midterm is due on Friday, 11:59 pm

- Remember there are **no 24-hour extension**
- Check your submission files (e.g. if you have more than one version, make sure you submit the right one)
- Grades for **homework 3 were posted**:
  - Check the point assignment in the comments and the files I returned.
  - Check the Homework 3 tab in the course website: Things to look out for.
- If you want to attend **office hours**, book early.

Last class

- Natural Experiments
  - How to identify them and how to think about potential confounding.
- Difference-in-Differences (DD):
  - How we can use two wrong estimates to get a right one.
  - Assumptions behind DD.
  - Staggered DD: See video for R code review.

Today

- Regression Discontinuity Design (RD):
  - How can we use discontinuities to recover causal effects?
  - Assumptions behind RD designs.
- Models with binary outcomes:
  - Linear Probability Models vs Logistic Models.

I'm on the edge [of glory?]

Another identification strategy

- We have seen:

RCTs

Selection on observables

Natural experiments

Differences-in-Differences

Regression Discontinuity Designs

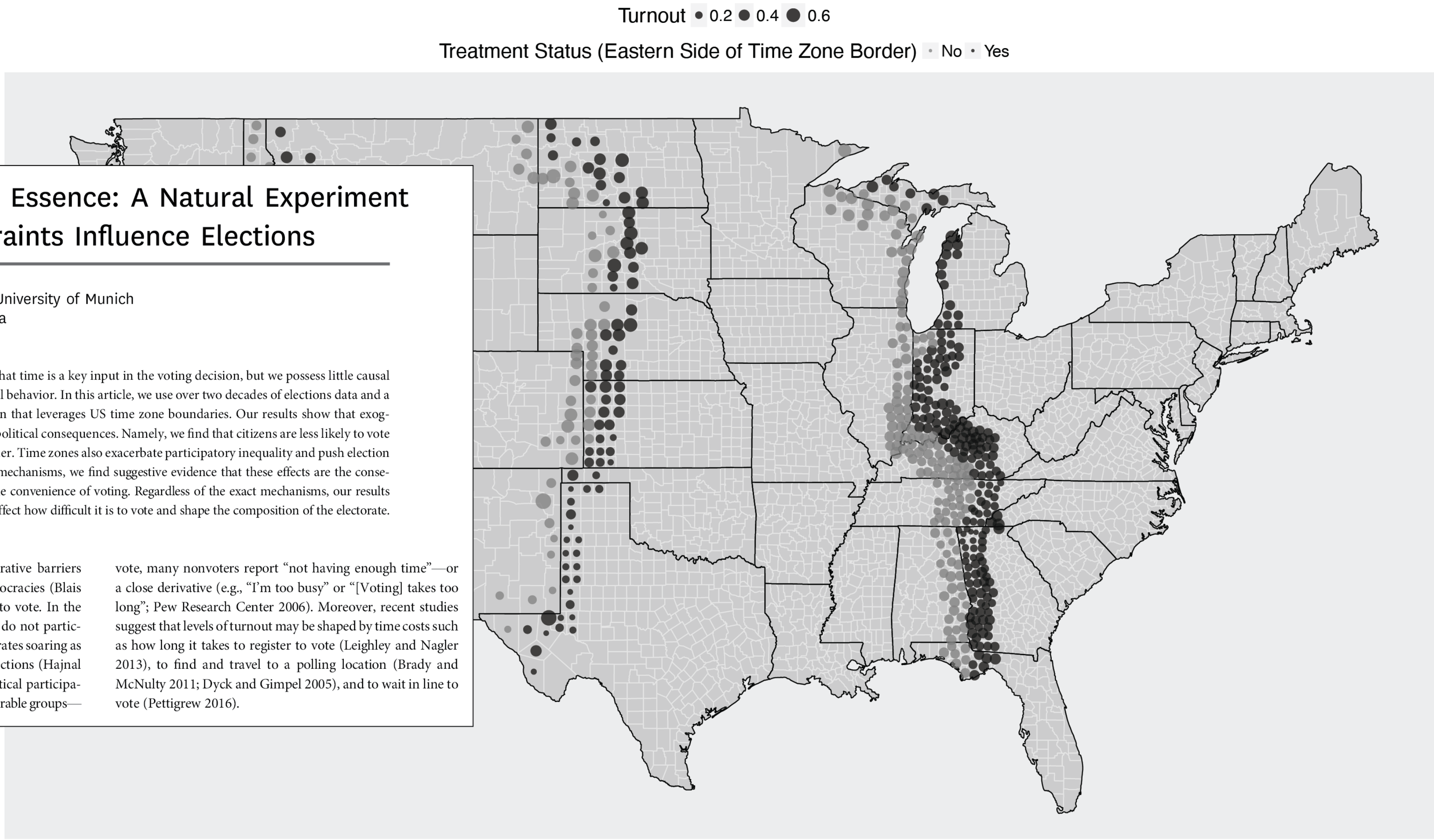
Introduction to Regression Discontinuity Designs

Regression Discontinuity (RD) Designs

Arbitrary rules determine treatment assignment

E.g.: If you are above a threshold, you are assigned to treatment, and if your below, you are not (or vice versa)

Geographic discontinuities



When Time Is of the Essence: A Natural Experiment on How Time Constraints Influence Elections

Jerome Schafer, Ludwig Maximilian University of Munich
John B. Holbein, University of Virginia

Foundational theories of voter turnout suggest that time is a key input in the voting decision, but we possess little causal evidence about how this resource affects electoral behavior. In this article, we use over two decades of elections data and a novel geographic regression discontinuity design that leverages US time zone boundaries. Our results show that exogenous shifts in time allocations have significant political consequences. Namely, we find that citizens are less likely to vote if they live on the eastern side of a time zone border. Time zones also exacerbate participatory inequality and push election results toward Republicans. Exploring potential mechanisms, we find suggestive evidence that these effects are the consequence of insufficient sleep and moderated by the convenience of voting. Regardless of the exact mechanisms, our results indicate that local differences in daily schedules affect how difficult it is to vote and shape the composition of the electorate.

Although in recent years the administrative barriers to voting have declined in many democracies (Blais 2010), many eligible citizens still fail to vote. In the United States, about 40% of registered voters do not participate in presidential elections, with abstention rates soaring as high as 60% in midterms and 70% in local elections (Hajnal and Trounstine 2016). Moreover, rates of political participation have remained stubbornly low among vulnerable groups—vote, many nonvoters report “not having enough time”—or a close derivative (e.g., “I’m too busy” or “[Voting] takes too long”; Pew Research Center 2006). Moreover, recent studies suggest that levels of turnout may be shaped by time costs such as how long it takes to register to vote (Leighley and Nagler 2013), to find and travel to a polling location (Brady and McNulty 2011; Dyck and Gimpel 2005), and to wait in line to vote (Pettigrew 2016).

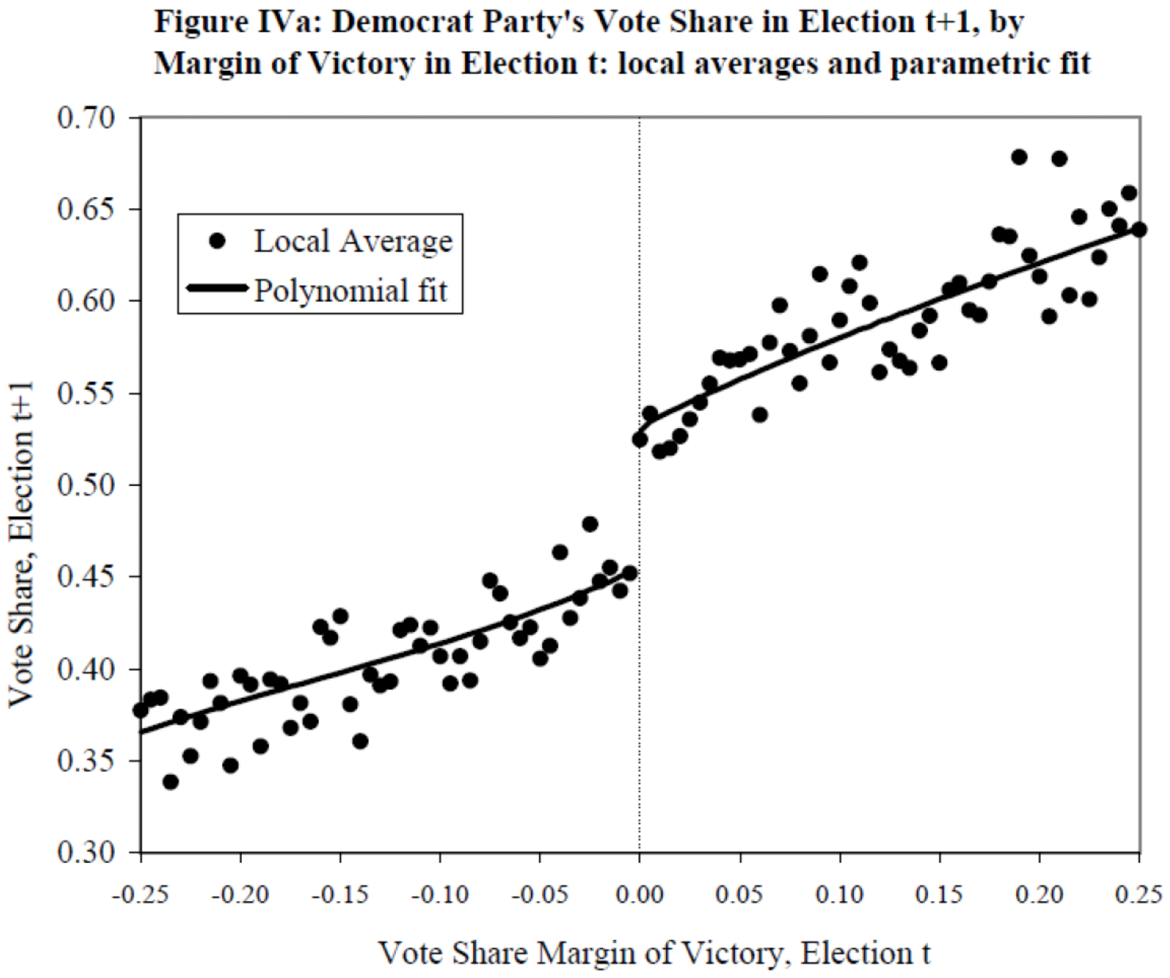
Time discontinuities

After Midnight: A Regression Discontinuity Design in Length of Postpartum Hospital Stays†

By Douglas Almond and Joseph J. Doyle Jr.*

Estimates of moral hazard in health insurance markets can be confounded by adverse selection. This paper considers a plausibly exogenous source of variation in insurance coverage for childbirth in California. We find that additional health insurance coverage induces substantial extensions in length of hospital stay for mother and newborn. However, remaining in the hospital longer has no effect on readmissions or mortality, and the estimates are precise. Our results suggest that for uncomplicated births, minimum insurance mandates incur substantial costs without detectable health benefits. (*JEL* D82, G22, I12, I18, J13)

Voting discontinuities



You can find discontinuities everywhere!

Key Terms

Running/ forcing variable

Index or measure that determines eligibility

Cutoff/ cutpoint/ threshold

Number that formally assigns you to a program or treatment

Hypothetical tutoring program

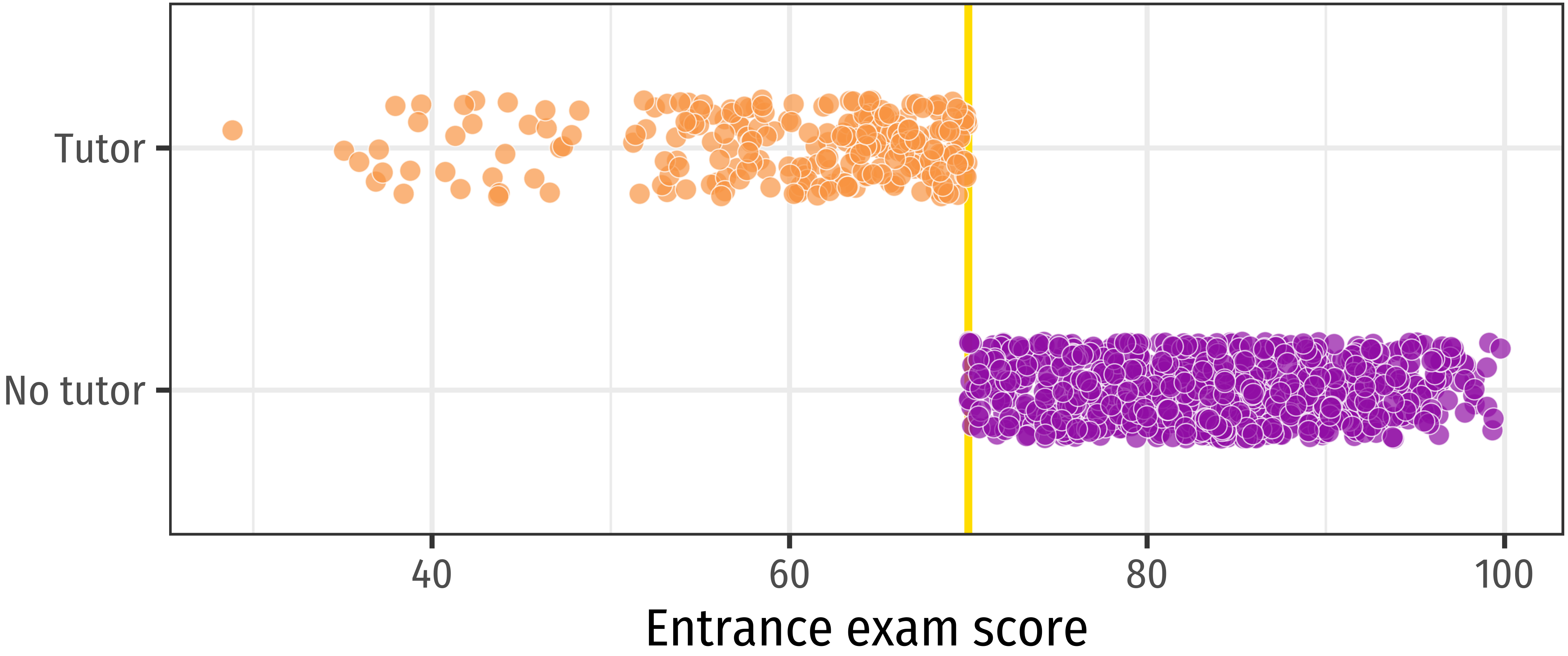
Students take an entrance exam

Those who score 70 or lower get a free tutor for the year

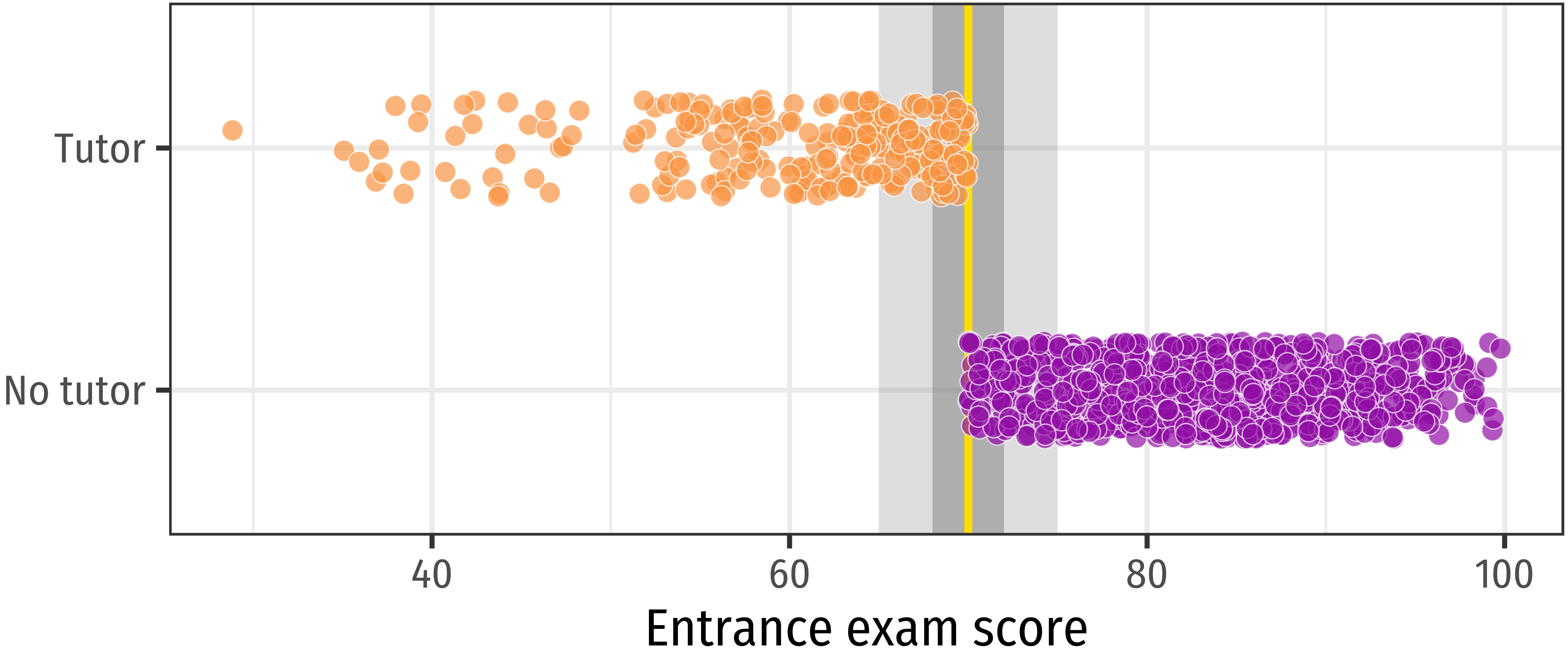
Students then take an exit exam at the end of the year

Can we compare students who got a tutor vs those that did not to capture the effect of having a tutor on GPA?

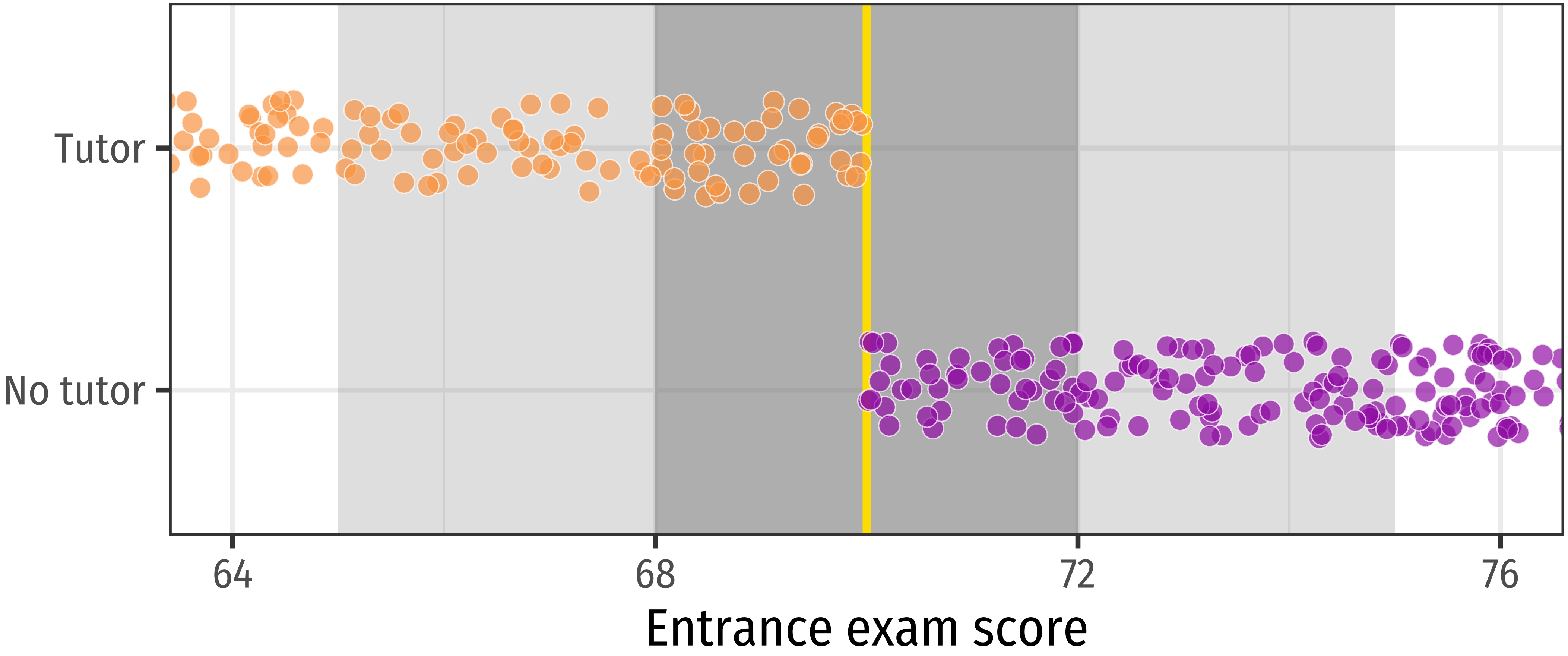
Assignment based on entrance score



Let's look at the area close to the cutoff



Let's get closer



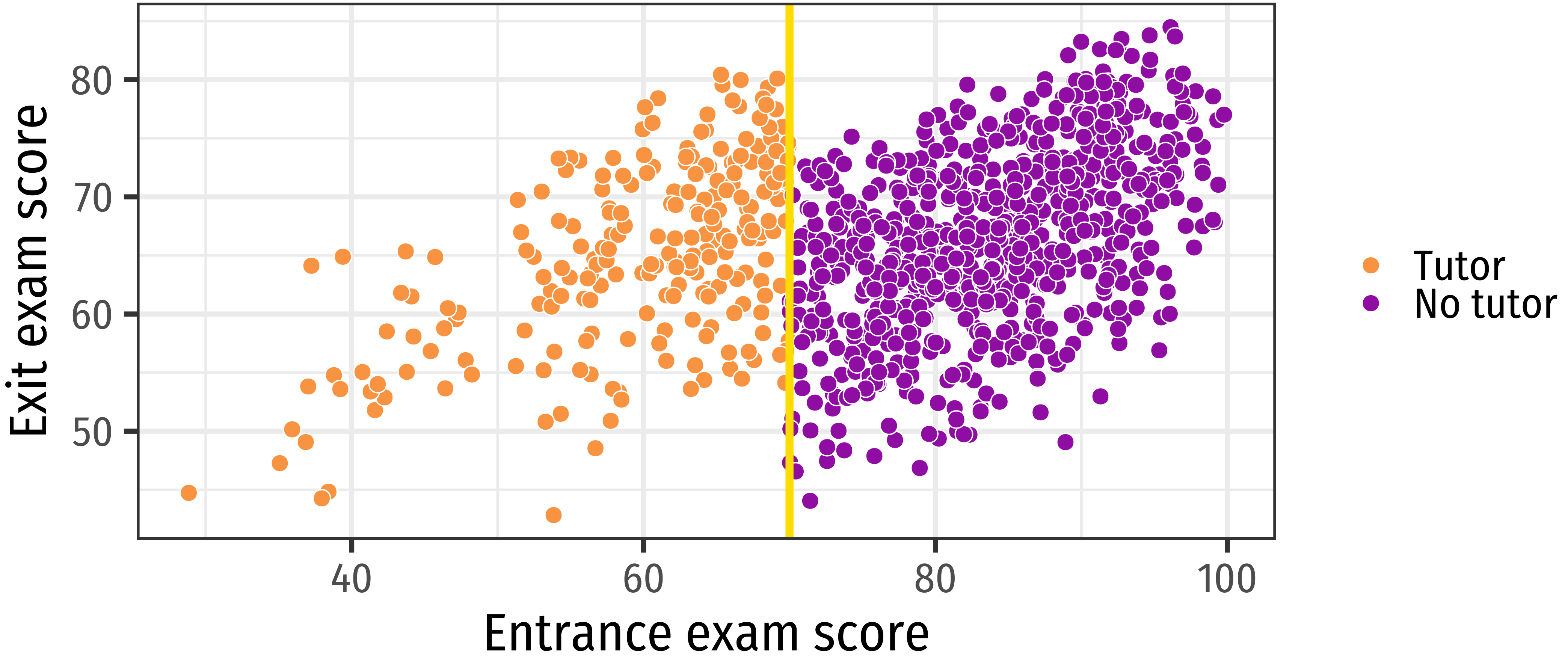
Causal inference intuition

Observations right before and after the threshold are essentially the same

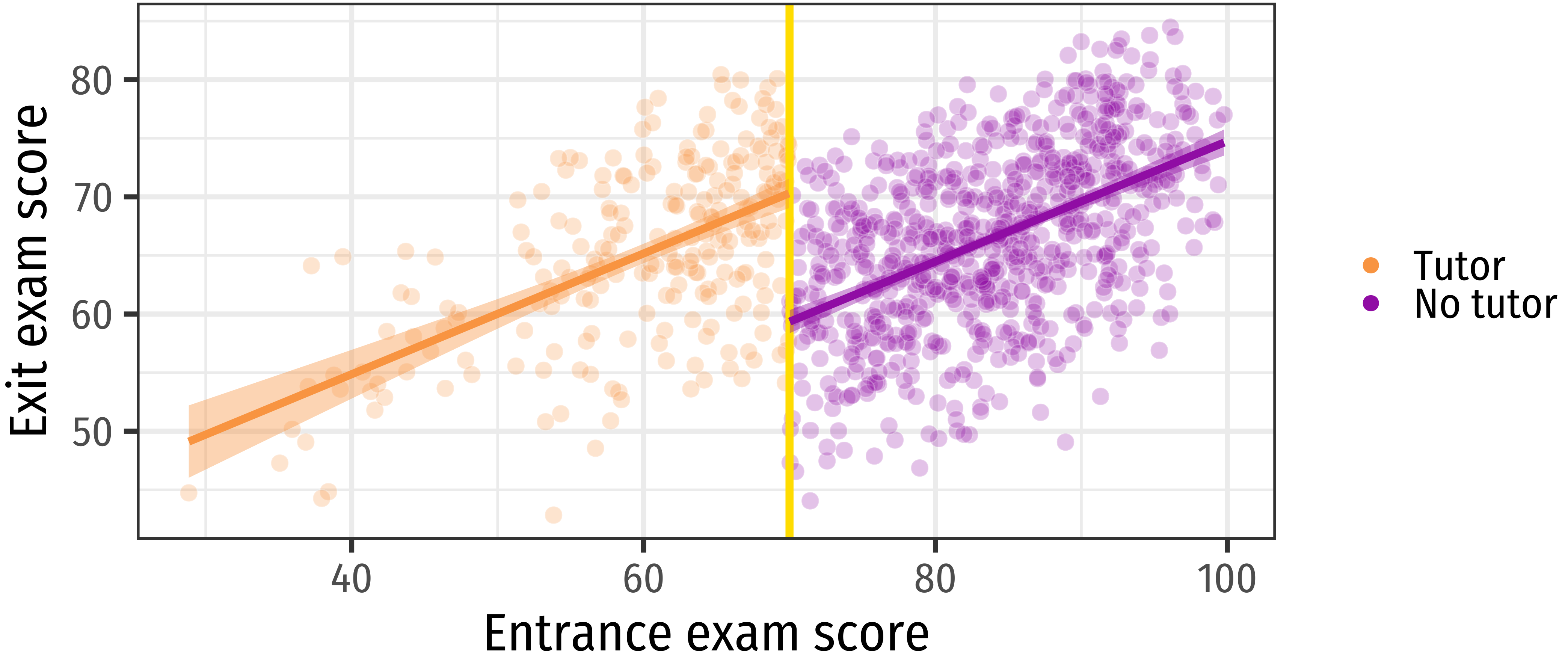
Pseudo treatment and control groups!

Compare outcomes right at the cutoff

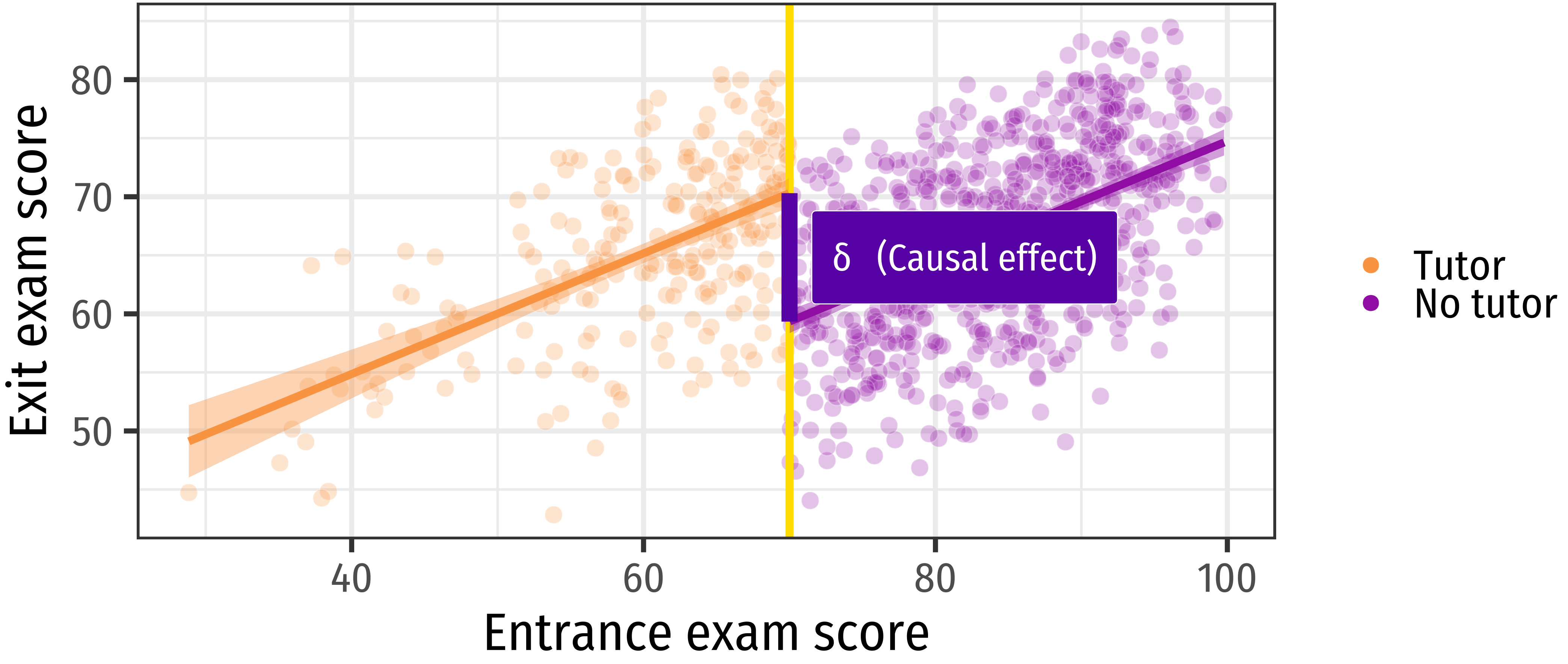
Exit exam results according to running variable



Fit a regression at the right and left side of the cutoff



Fit a regression at the right and left side of the cutoff



Let's get [a bit] math-y...

Behind the scenes of RDs

- Basically, regression discontinuities work under an **asymptotic assumption**:

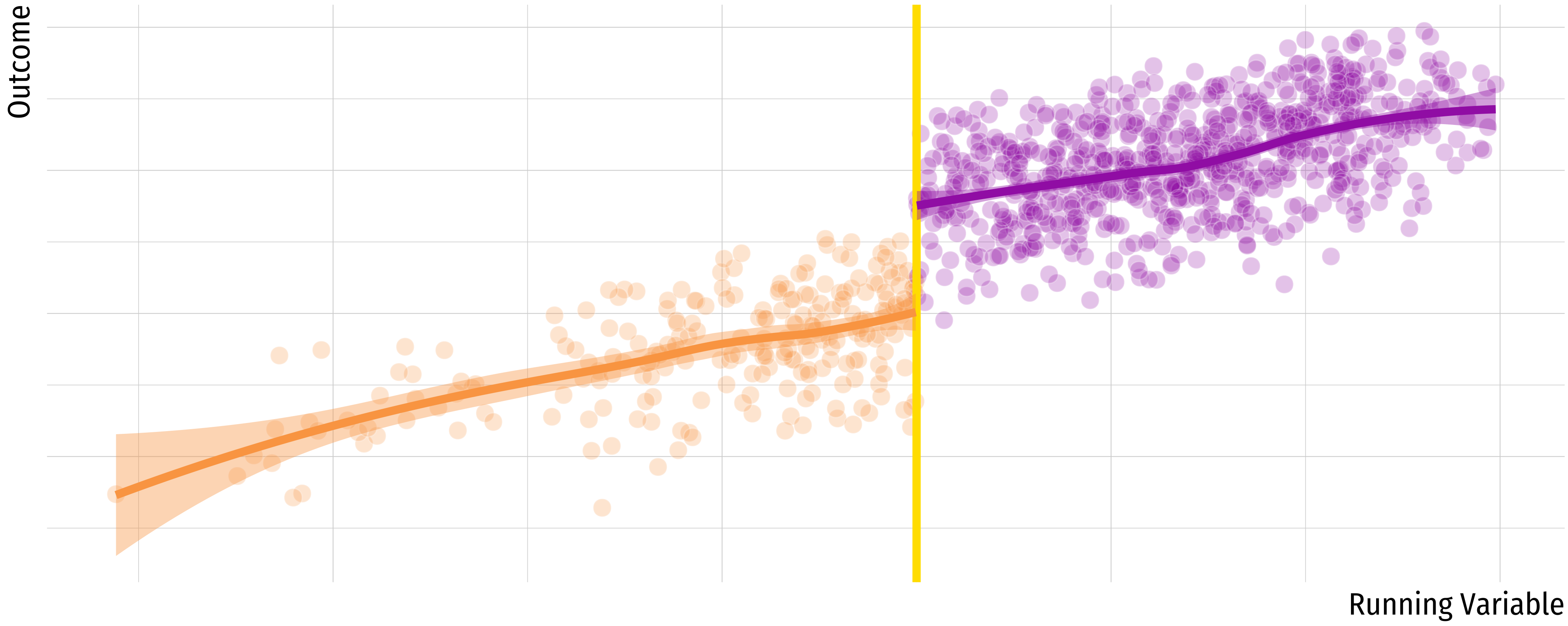
- Let Y_i be the outcome of interest, Z_i the treatment assignment, R_i the running variable, and c the cutoff score:

$$Z_i = \begin{cases} 0 & R_i \leq c \\ 1 & R_i > c \end{cases}$$

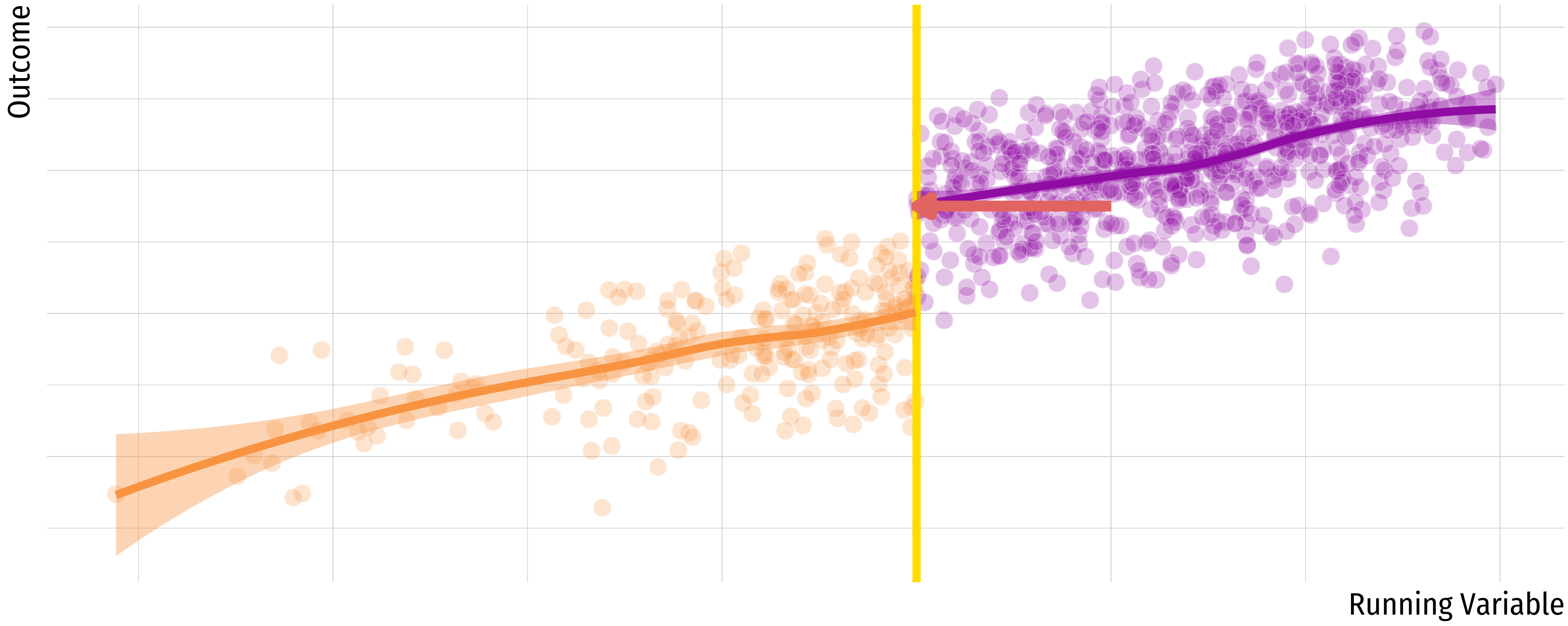
- Then, we can define the treatment effect δ as:

$$\delta = \lim_{\epsilon \to 0^+} E[Y_i | R_i = c + \epsilon] - \lim_{\epsilon \to 0^-} E[Y_i | R_i = c + \epsilon]$$

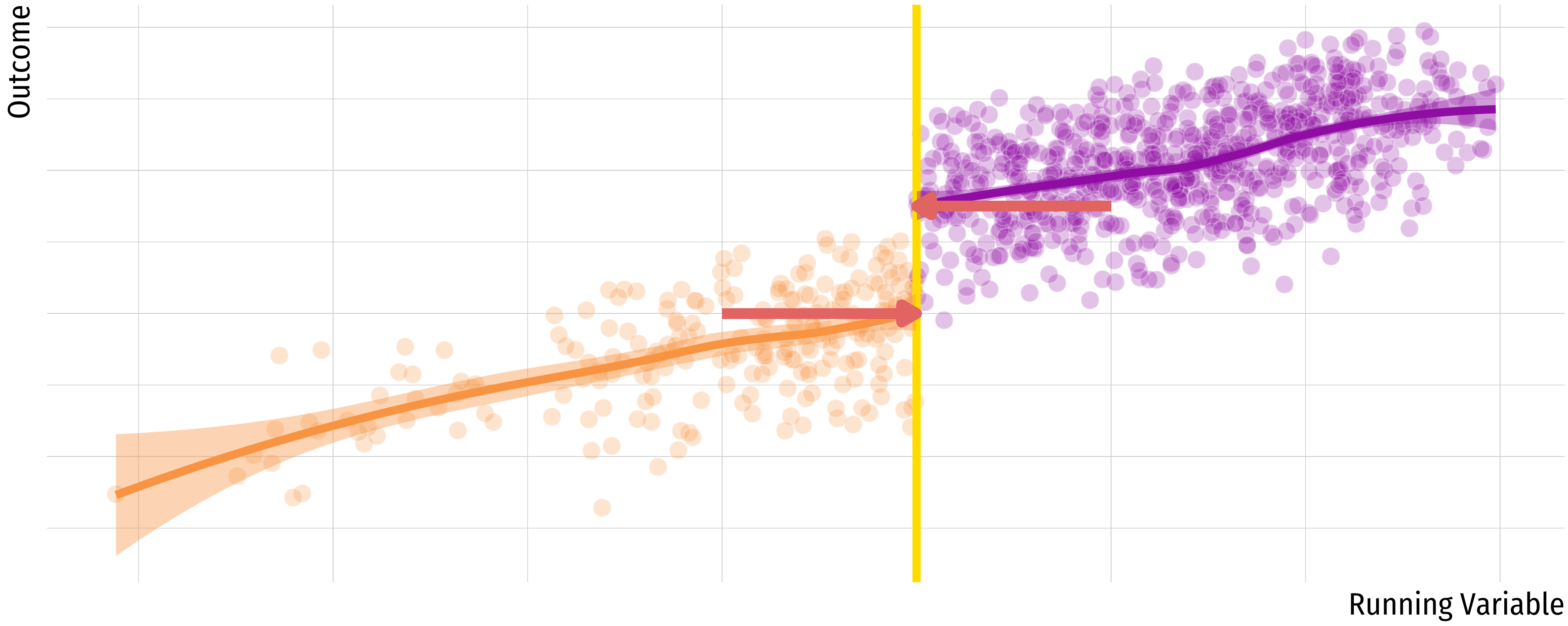
What does the limit expression mean?



What does the limit expression mean?



What does the limit expression mean?



What is the estimand we are estimating?

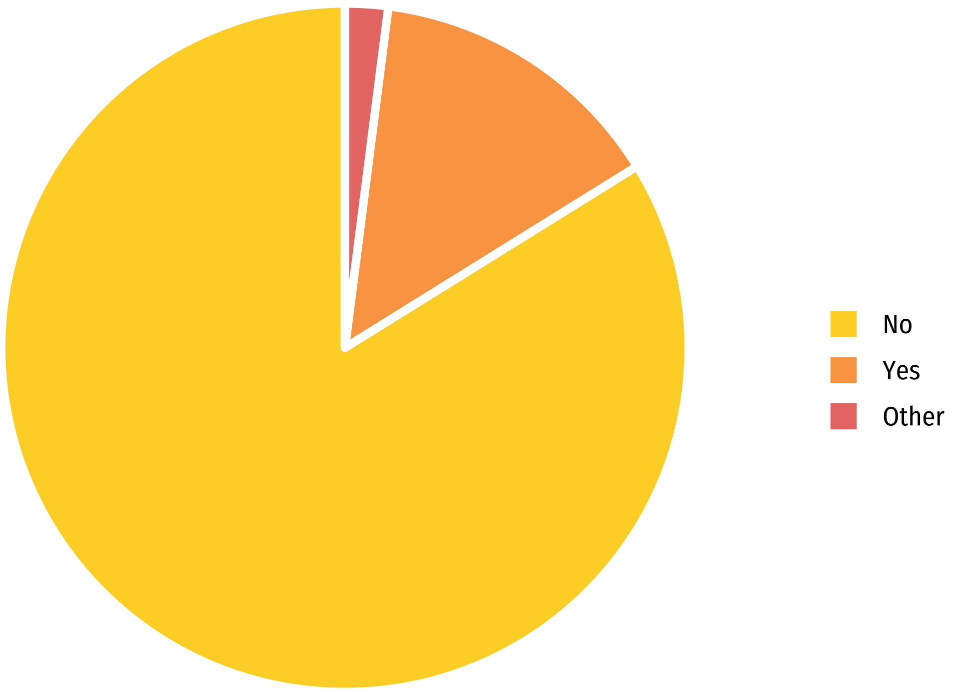
Local Average Treatment Effect (LATE) for units at R=c

Is that what we want?

Probably not ideal, there may not be *any* units with R=c

... but better LATE than nothing!

JITT: Can we estimate an effect for R=25 vs R=75?



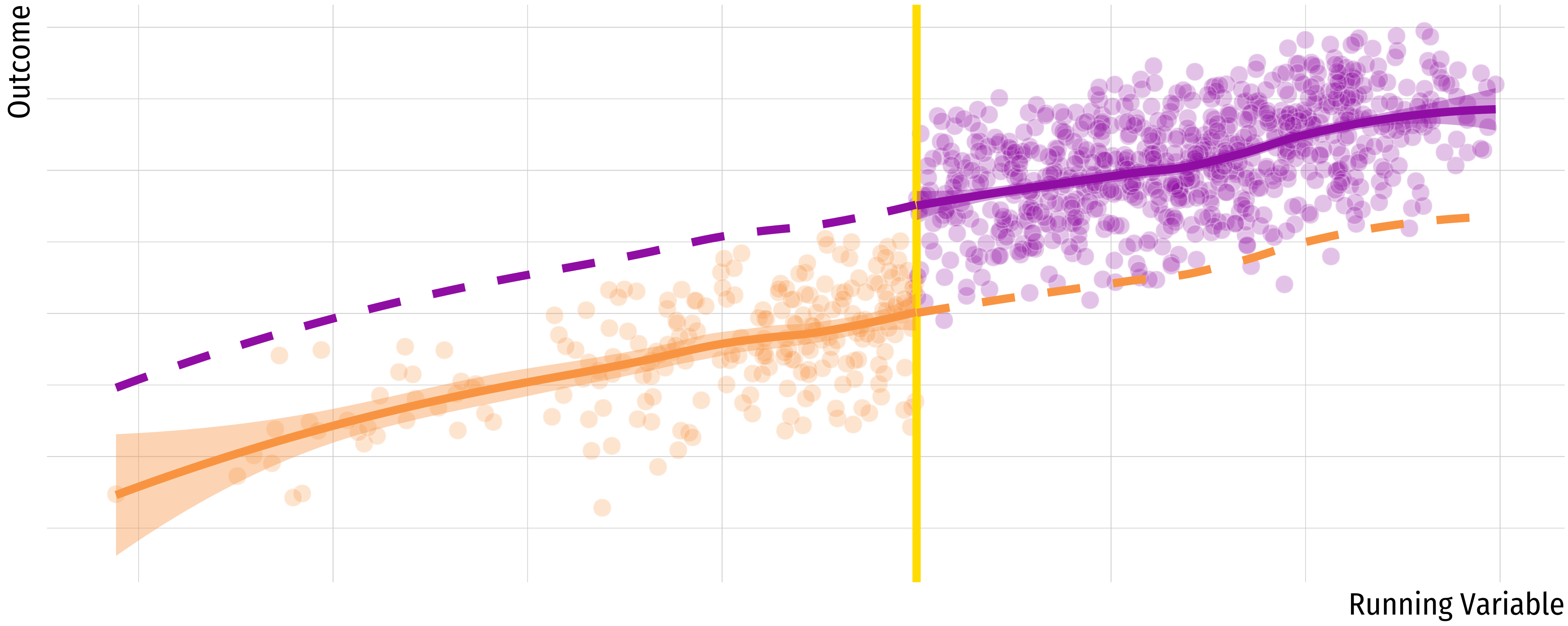
Conditions required for identification

- Threshold rule **exists** and cutoff point is **known**
- The running variable R_i is **continuous** near c.
- Key assumption:

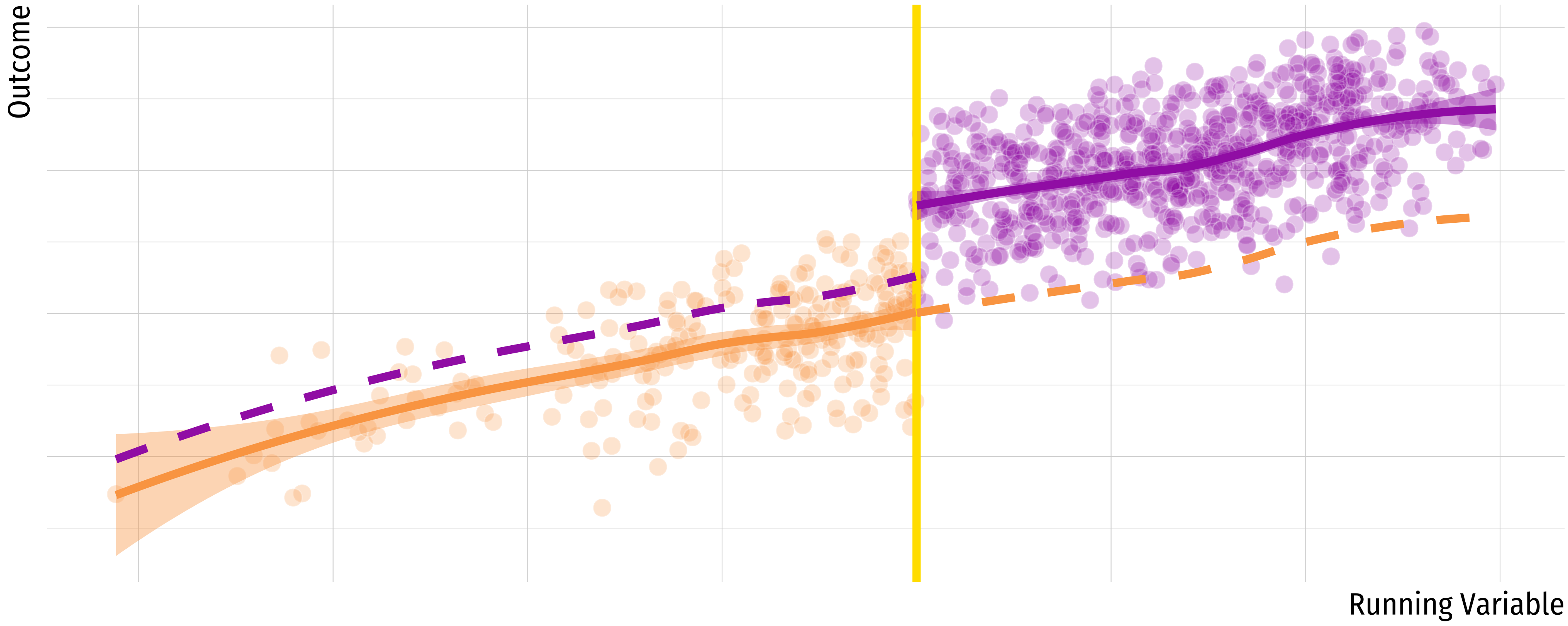
Continuity of E[Y(1)|R] and E[Y(0)|R] at R=c

That's the math-y way to say what most of you answered on the JITT!

Potential outcomes need to be smooth across the threshold



Potential outcomes need to be smooth across the threshold



Can you think situations where that could happen?

How can I check if this assumption holds?

You can't! (it's an assumption)

Robustness checks:

- Check density across the cutoff
- Check RD for covariates

Estimation in practice

How do we actually estimate an RD?

- The simplest way to do this is to fit a regression:

$$Y_i = \beta_0 + \beta_1(R_i - c) + \beta_2\mathrm{I}[R_i > c] + \beta_3(R_i - c)\mathrm{I}[R_i > c]$$

How do we actually estimate an RD?

- The simplest way to do this is to fit a regression:

$$Y_i = \beta_0 + \beta_1 \underbrace{(R_i - c)}_{\text{Distance to the cutoff}} + \beta_2 \mathrm{I}[R_i > c] + \beta_3 \overbrace{(R_i - c)}^{\text{Distance to the cutoff}} \mathrm{I}[R_i > c]$$

How do we actually estimate an RD?

- The simplest way to do this is to fit a regression:

$$Y_i = \beta_0 + \beta_1(R_i - c) + \beta_2 \underbrace{\mathbb{I}[R_i > c]}_{\text{Treatment}} + \beta_3(R_i - c)\overbrace{\mathbb{I}[R_i > c]}^{\text{Treatment}}$$

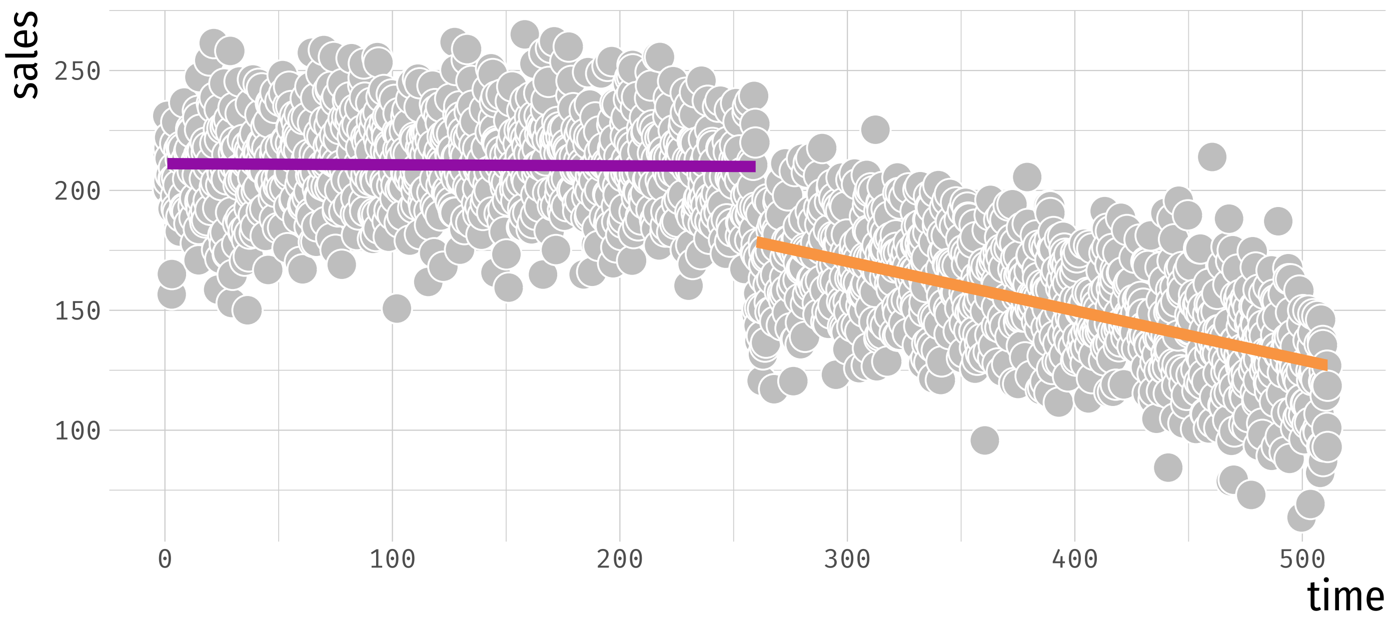
- You want to add **flexibility** for each side of the cutoff.

Can you identify these parameters in a plot?

Let's see some examples: Sales using a linear model

```
sales <- sales %>% mutate(dist = c-time)

lm(sales ~ dist + treat + dist*treat, data = sales)
```



Let's see some examples: Sales using a linear model

```
summary(lm(sales ~ dist + treat + dist*treat, data = sales))
```

```
##
## Call:
## lm(formula = sales ~ dist + treat + dist * treat, data = sales)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -65.738 -13.940   0.051  13.538  76.515
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 178.640954   1.300314  137.38   <2e-16 ***
## dist          0.205355   0.008882   23.12   <2e-16 ***
## treat        31.333952   1.842338   17.01   <2e-16 ***
## dist:treat   -0.200845   0.012438  -16.15   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.52 on 1996 degrees of freedom
## Multiple R-squared:  0.6939,    Adjusted R-squared:  0.6934
## F-statistic:  1508 on 3 and 1996 DF,  p-value: < 2.2e-16
```

We can be more flexible

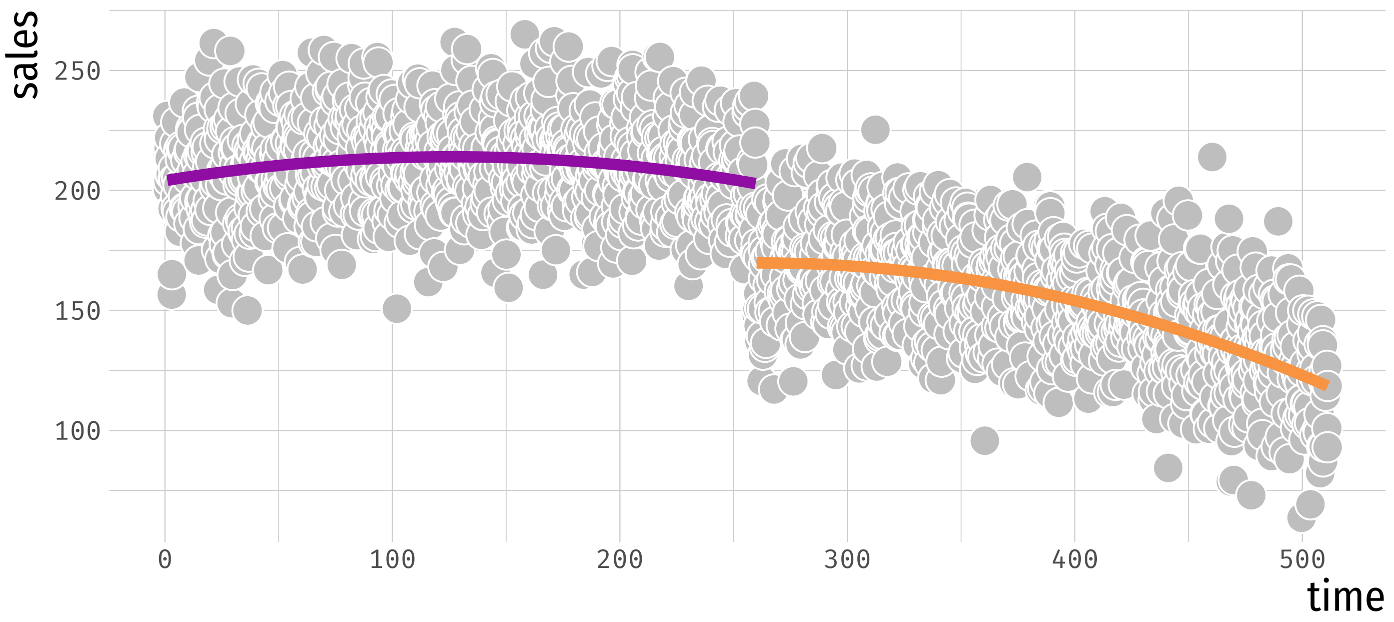
- The previous example just included linear terms, but you can also be more flexible:

$$Y_i = \beta_0 + \beta_1 f(R_i - c) + \beta_2 \mathrm{I}[R_i > c] + \beta_3 f(R_i - c)\mathrm{I}[R_i > c]$$

- Where f is any function you want.

What happens if we fit a quadratic model?

```
lm(sales ~ dist + I(dist^2) + treat + dist*treat + treat*I(dist^2), data = sales)
```



What happens if we fit a quadratic model?

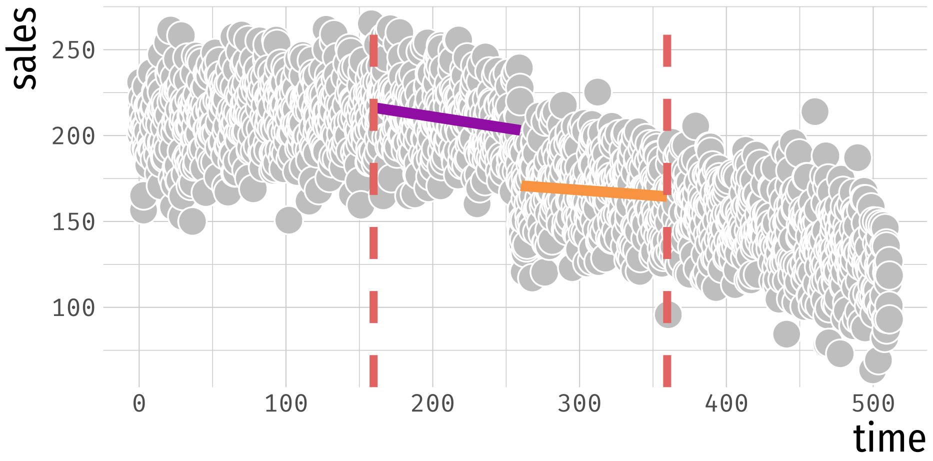
```
summary(lm(sales ~ dist + I(dist^2) + treat + dist*treat + treat*I(dist^2), data = sales))
```

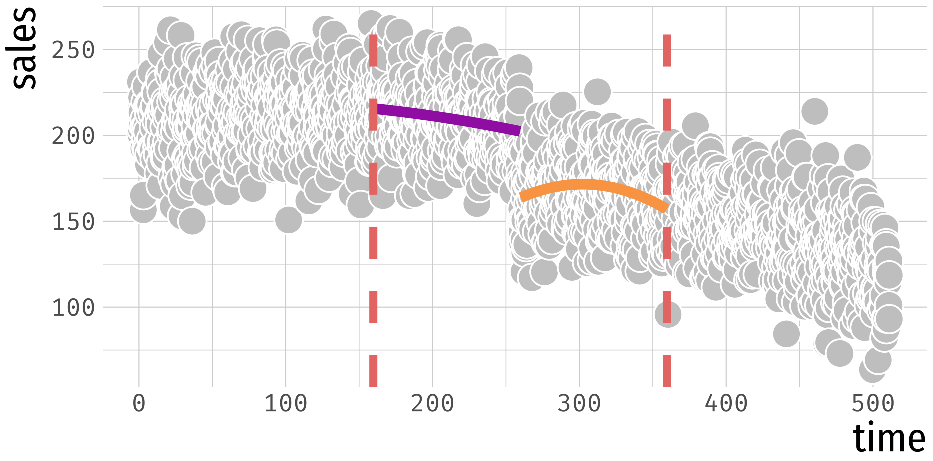
```
##
## Call:
## lm(formula = sales ~ dist + I(dist^2) + treat + dist * treat +
##     treat * I(dist^2), data = sales)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -66.090 -13.979   0.239  13.154  76.656
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.698e+02  1.937e+00  87.665  < 2e-16 ***
## dist            -4.302e-03  3.556e-02  -0.121 0.903725
## I(dist^2)       -8.288e-04  1.363e-04  -6.083 1.41e-09 ***
## treat            3.308e+01  2.747e+00  12.041  < 2e-16 ***
## dist:treat       1.713e-01  4.964e-02   3.452 0.000569 ***
## I(dist^2):treat  2.034e-04  1.877e-04   1.084 0.278554
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.23 on 1994 degrees of freedom
## Multiple R-squared:  0.7029,    Adjusted R-squared:  0.7021
## F-statistic: 943.5 on 5 and 1994 DF,  p-value: < 2.2e-16
```

What happens if we only look at observations close to c?

```
sales_close <- sales %>% filter(dist>-100 & dist<100)

lm(sales ~ dist + treat + dist*treat + treat, data = sales_close)
lm(sales ~ dist + I(dist^2) + treat + dist*treat + treat*I(dist^2), data = sales_close)
```





How do they compare?

```
summary(lm(sales ~ dist + treat + dist*treat + treat, data = sales_close))
```

```
##
## Call:
## lm(formula = sales ~ dist + treat + dist * treat + treat, data = sales_close)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -53.241 -14.764   0.268  12.938  57.811
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 170.84457    2.05528  83.125   <2e-16 ***
## dist          0.06345    0.03542   1.791   0.0736 .
## treat        32.21243    2.93614  10.971   <2e-16 ***
## dist:treat    0.06909    0.05047   1.369   0.1714
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.25 on 782 degrees of freedom
## Multiple R-squared:  0.5261,    Adjusted R-squared:  0.5243
## F-statistic: 289.4 on 3 and 782 DF,  p-value: < 2.2e-16
```

How do they compare?

```
summary(lm(sales ~ dist + I(dist^2) + treat + dist*treat + treat*I(dist^2), data = sales_close))
```

```
##
## Call:
## lm(formula = sales ~ dist + I(dist^2) + treat + dist * treat +
##     treat * I(dist^2), data = sales_close)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -50.080 -14.238  -0.463  12.740  54.231
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     163.550012   3.001833  54.483  < 2e-16 ***
## dist             -0.375526   0.136936  -2.742 0.006240 **
## I(dist^2)        -0.004415   0.001331  -3.317 0.000951 ***
## treat            38.757140   4.316684   8.978  < 2e-16 ***
## dist:treat        0.552254   0.195847   2.820 0.004927 **
## I(dist^2):treat   0.003975   0.001894   2.099 0.036121 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.13 on 780 degrees of freedom
## Multiple R-squared:  0.5328,	Adjusted R-squared:  0.5298
## F-statistic: 177.9 on 5 and 780 DF,  p-value: < 2.2e-16
```

Potential problems

- There are **many potential problems** with the previous examples:
  - Which polynomial function should we choose? Linear, quadratic, other?
  - What bandwidth should we choose? Whole sample? [-100,100]?

- There are some ways to address these concerns.

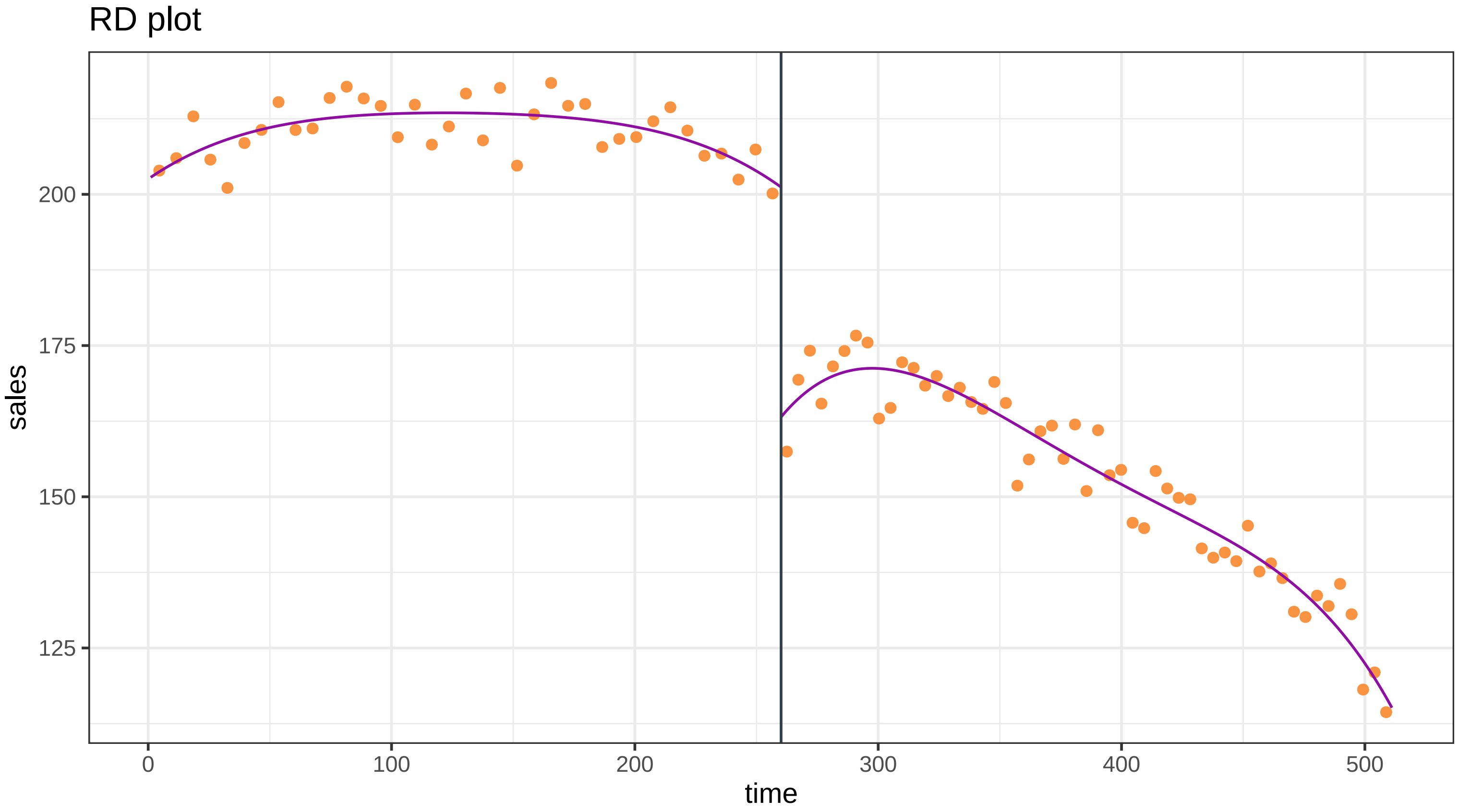
Icons made by Freepik from www.flaticon.com

Package `rdrobust`

- Robust Regression Discontinuity introduced by Cattaneo, Calonico, Farrell & Titiunik (2014).
- Use of local polynomial for fit.
- Data-driven optimal bandwidth (bias vs variance).
- `rdrobust`: Estimation of LATE and opt. bandwidth
- `rdplot`: Plotting RD with nonparametric local polynomial.

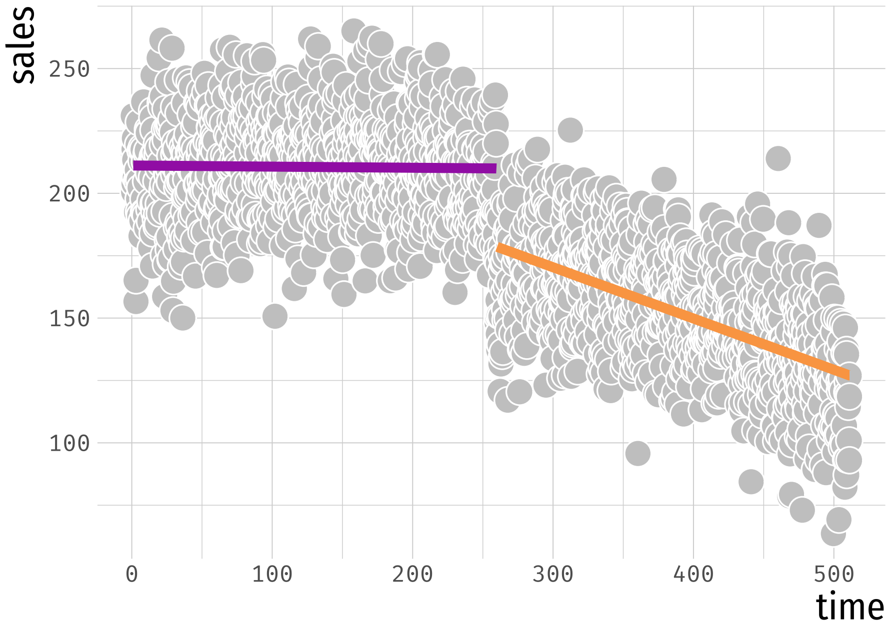
Let's compare with previous parametric results

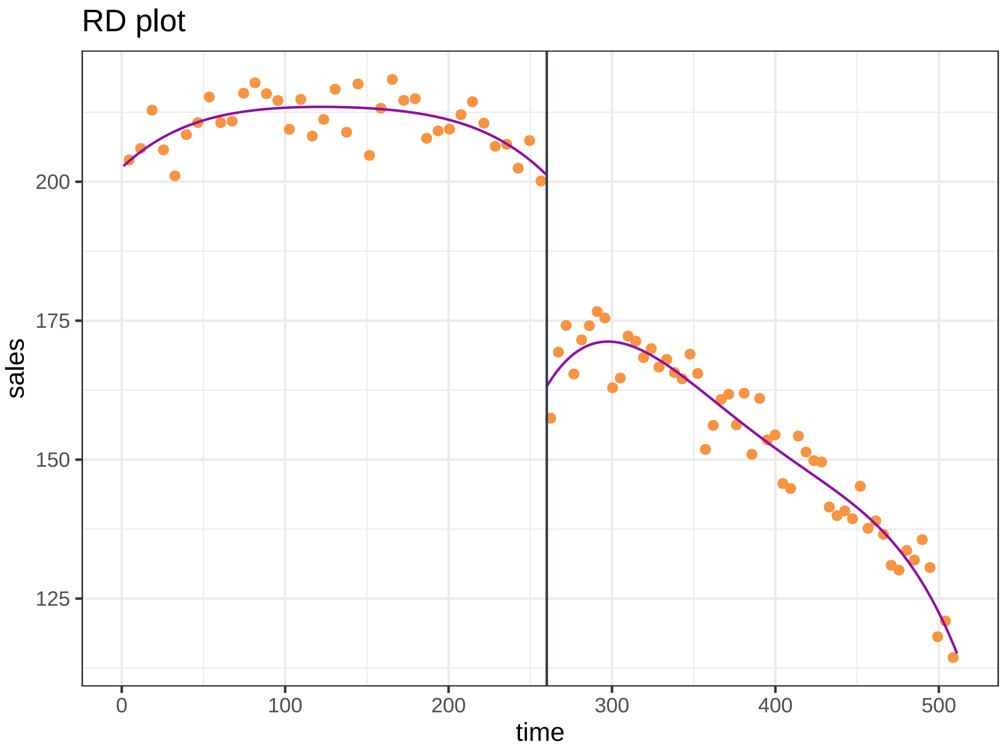
```
rdplot(y = sales$sales, x = sales$time, c = c,
       title = "RD plot", x.label = "time", y.label = "sales")
```



Let's compare with previous parametric results

```r
rdplot(y = sales$sales, x = sales$time, c = c,
       title = "RD plot", x.label = "time", y.label = "sales")
```





Let's compare with previous parametric results

```
summary(rdrobust(y = sales$sales, x = sales$time, c = c))
```

```
## Call: rdrobust
##
## Number of Obs.                  2000
## BW type                        mserd
## Kernel                    Triangular
## VCE method                        NN
##
## Number of Obs.                 1000         1000
## Eff. Number of Obs.             202          213
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  54.304       54.304
## BW bias (b)                  87.787       87.787
## rho (h/b)                     0.619        0.619
## Unique Obs.                    1000         1000
##
## =============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## =============================================================================
##   Conventional   -37.434     4.344    -8.618     0.000   [-45.948 , -28.921]
##         Robust         -         -    -7.610     0.000   [-48.596 , -28.691]
## =============================================================================
```

How do we weight observations?

- `rdrobust` uses `rdbwselect()` function (by default) to estimate a data-driven bandwidth (i.e. what observations we are going to use for estimation).
    - If we use a bandwidth, does this mean that the RD is estimating an effect for that population within the bandwidth?
- Kernels are also important in this context:
    - How do I weight observations within the bandwidth (e.g. uniform, triangle)

Observing kernels

Takeaway points

- RD designs are **great** for causal inference!
  - Strong internal validity
  - Number of robustness checks
- **Limited** external validity.
- Make sure to check your data:
  - Discontinuity in treatment assignment
  - Density across the cutoff
  - Smoothness of covariates

References

- Angrist, J. and S. Pischke. (2015). "Mastering Metrics". *Chapter 4*.
- Calonico, Cattaneo and Titiunik. (2015). "rdrobust: An R Package for Robust Nonparametric Inference in Regression-Discontinuity Designs". R Journal 7(1): 38-51.
- Heiss, A. (2020). "Program Evaluation for Public Policy". *Class 10: Regression Discontinuity I, Course at BYU*.
- Lee, D. and T. Lemieux. (2010). "Regression Discontinuity in Economics". *Journal of Economic Literature 48, pp 281-355*.