

# Regression Discontinuity

INFO/STSCI/ILRST 3900: Causal Inference

28 Oct 2025

# Learning goals for today

At the end of class, you will be able to:

1. Explain how discontinuities can be exploited for causal identification
2. Understand bias variance trade-off in selecting bandwidths

# Logistics

- ▶ PSET 4 Peer Review due Nov 4
- ▶ Quiz 4 on Nov 4

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- ▶ Students who score above a state specific threshold get **Certificate of Merit**
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- ▶ Data contains 5,126 Certificate of Merit winners and 2,848 letters of commendation winners

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What is the causal effect of the CoM on various attributes?

# What is the effect of a scholarship?

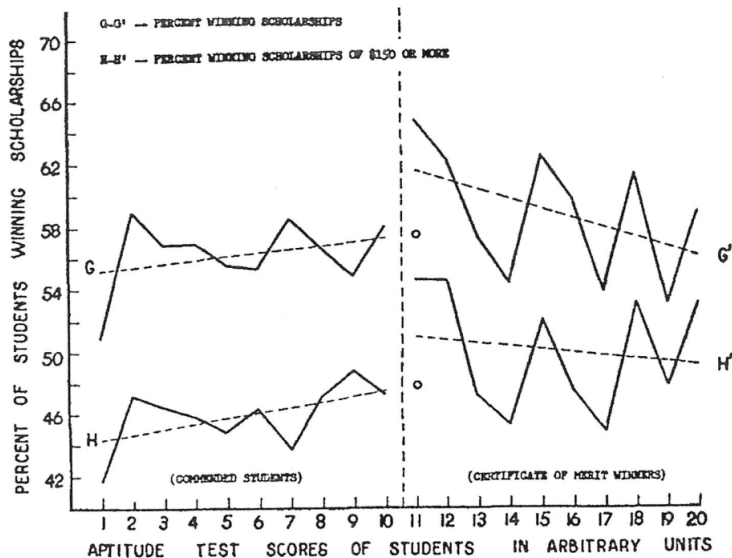


FIG. 2. Regression of success in winning scholarships on exposure determiner.

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SQT

CoM  $\longrightarrow$  Other Scholarships

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- ▶ Matching:
  - Match each person who received Certificate of Merit with a “similar” person who received Letter of Recommendation
- ▶ In both cases,  $P(\text{CoM} = 1 \mid \text{Score}) = 0$  for some scores
- ▶ Violates Positivity Assumption

$$P(A = a \mid L = \ell) > 0 \quad \text{for each } a \text{ and } \ell$$

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- ▶ Let's aim for an easier target
- ▶ Average Treatment effect for individuals at the cut-off

$$\textbf{Local ATE} = E(Y_i^{a=1} \mid \text{Score} = c) - E(Y_i^{a=0} \mid \text{Score} = c_0)$$

- ▶ Does not tell us about treatment effect for everyone!

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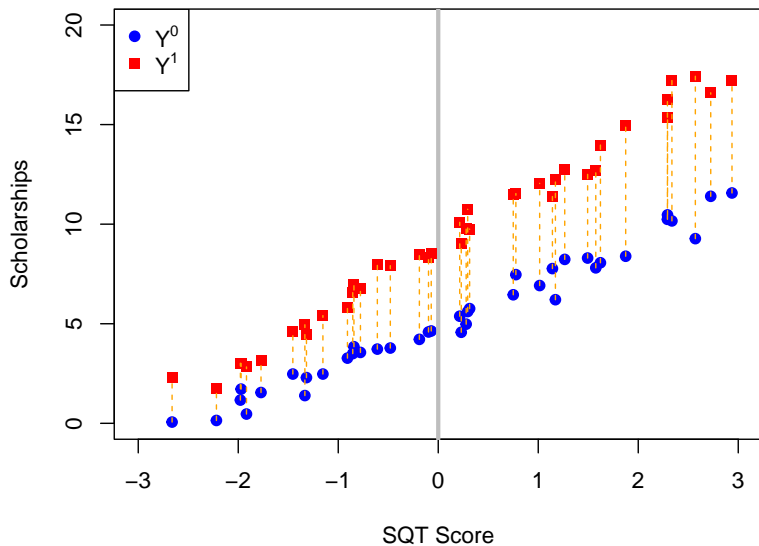
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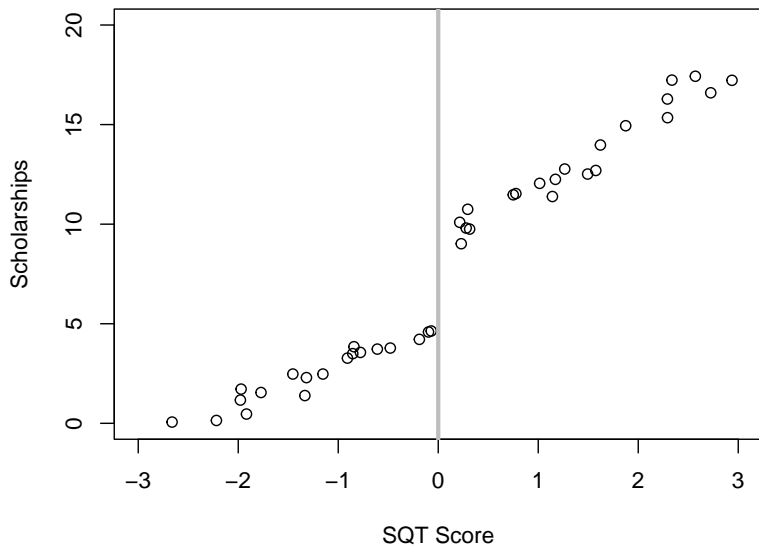
- ▶ Using observed data, estimate,  $E(Y | R = r)$  for  $r$  closer and closer to the cut-off
- ▶ Estimate local ATE  $E(Y_i^{a=1} | R_i = c) - E(Y_i^{a=0} | X_i = c)$  by

$$\underbrace{\lim_{x \rightarrow c^+} E(Y | X = x)}_{\text{from above the cut-off}} - \underbrace{\lim_{x \rightarrow c^-} E(Y | X = x)}_{\text{from below the cut-off}}$$

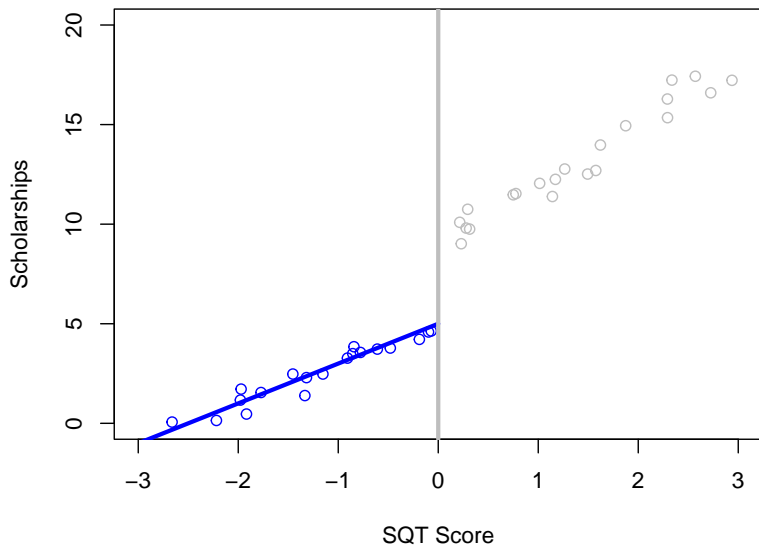
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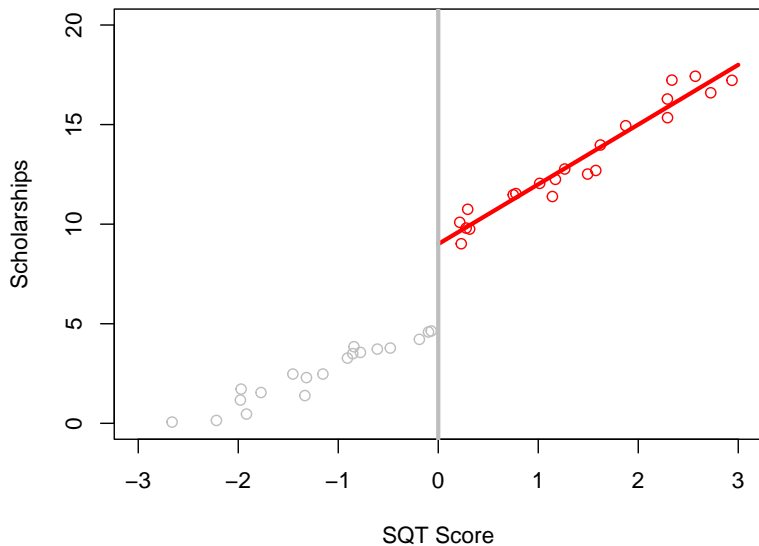
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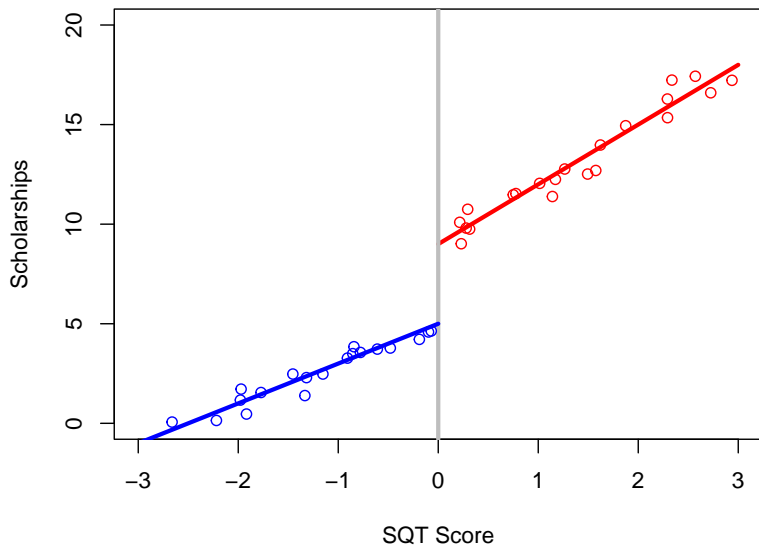


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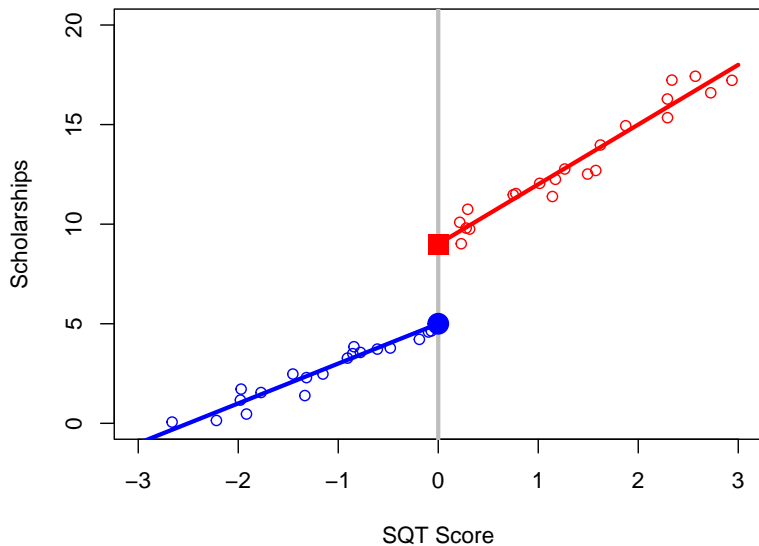




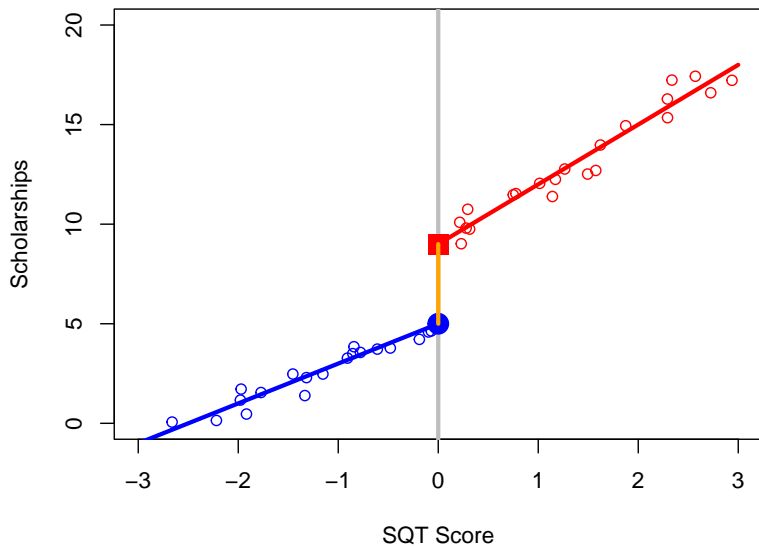
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- ▶ Ending up above or below the threshold is more or less chance  
Scoring 100.1 vs 99.9 is essentially random
- ▶ Conditional exchangeability holds for people very close to the cut-off
- ▶ Conditional exchangeability does not hold for people further from the cut-off

# Discontinuities in the wild

Discontinuities turn up in lots of places...

- ▶ Enrollment in flagship state universities may require certain test scores<sup>1</sup>

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- ▶ Medicare eligibility requires age to be 65+<sup>3</sup>
- ▶ ...

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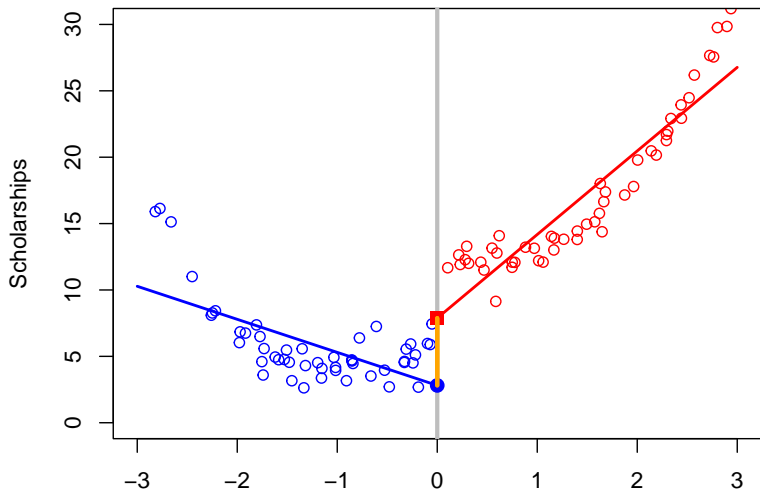
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# Non-linear settings

What if  $E(Y^{a=1} \mid X)$  is non-linear?

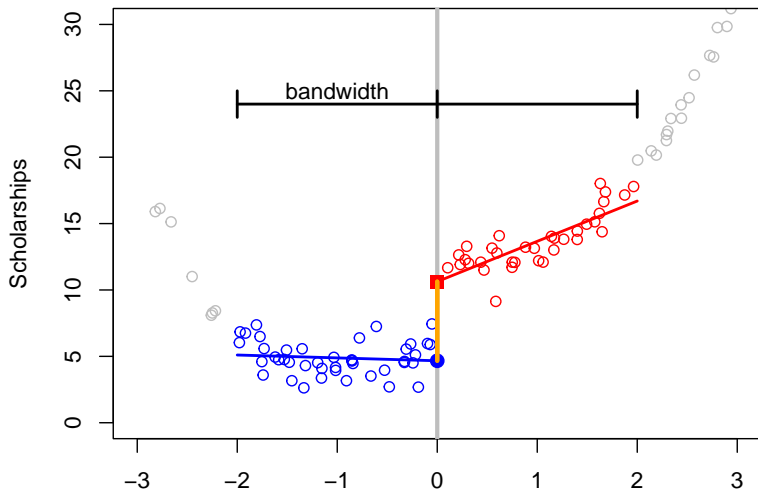
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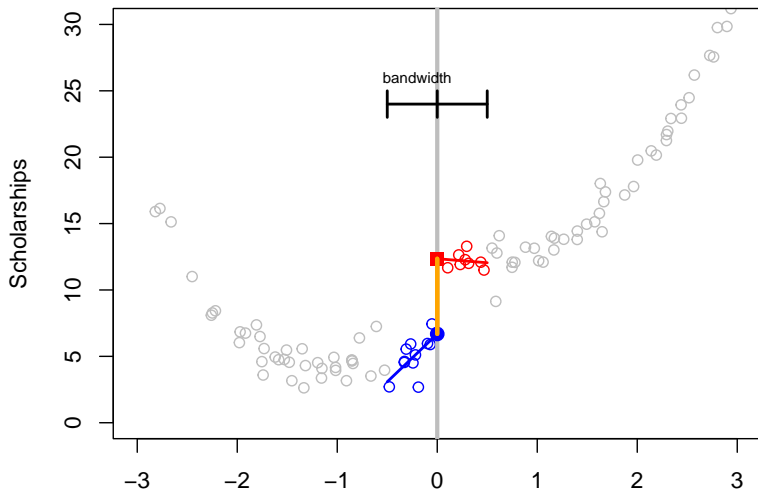
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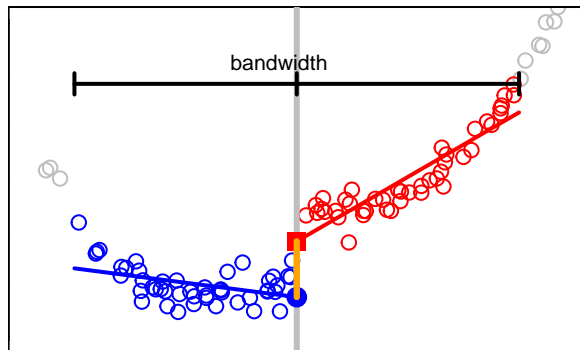


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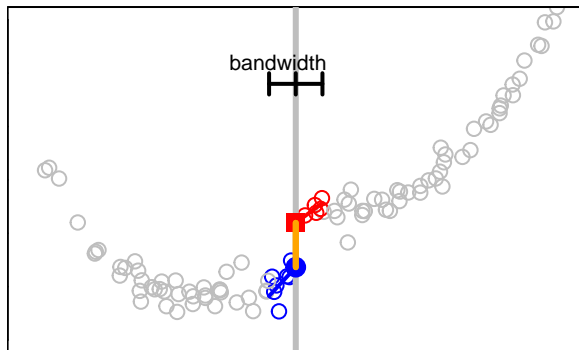


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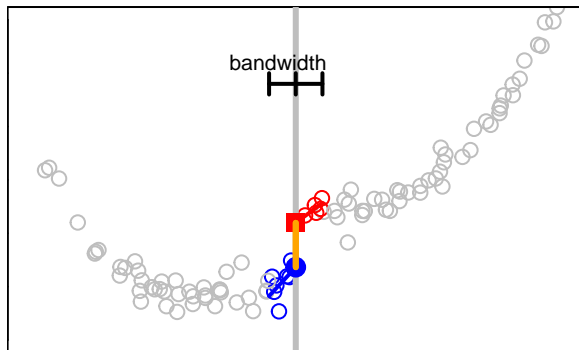
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- ▶ Bias: how far off of the truth in infinite data?
- ▶ Variance: how much would my estimate change in new sample?
- ▶ Roughly speaking, bandwidth should be smaller when your data set is larger

# Regression discontinuity

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## Pros:

- ▶ Very few assumptions required
- ▶ Plausible in many real applications

## Cons:

- ▶ Can only estimate local ATE, does not generalize well
- ▶ Results depend on picking a bandwidth

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