Regression discontinuity designs

Intermediate Social Statistics

Week 6 (21 February 2017)

Andy Eggers

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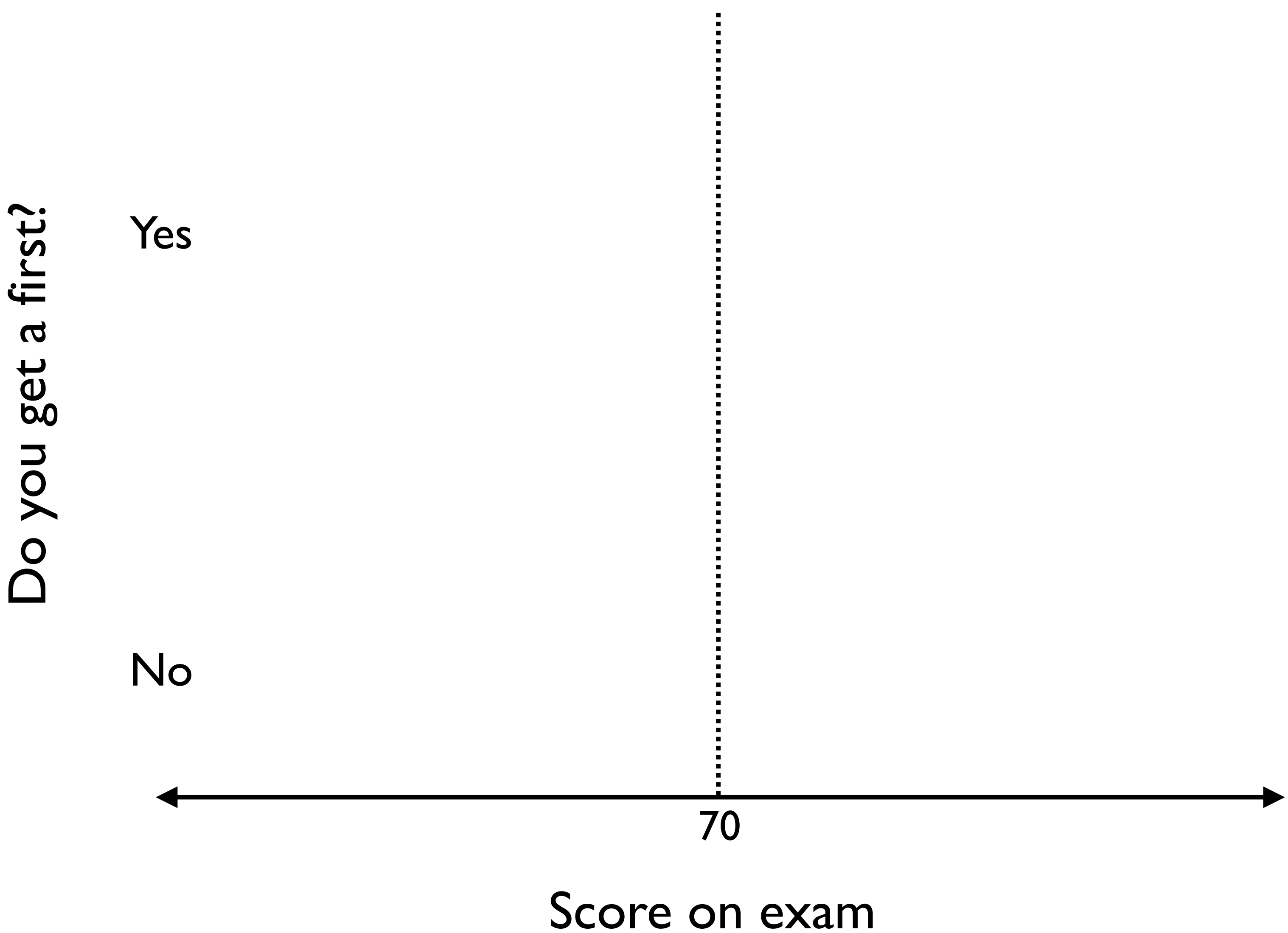
- French municipalities use PR elections if population is 3,500 (now 1,000) or higher
- A candidate is elected if she receives more votes than any other candidate
- Journalists report a recession if the economy shrinks for two consecutive quarters

“Policies” make jumps



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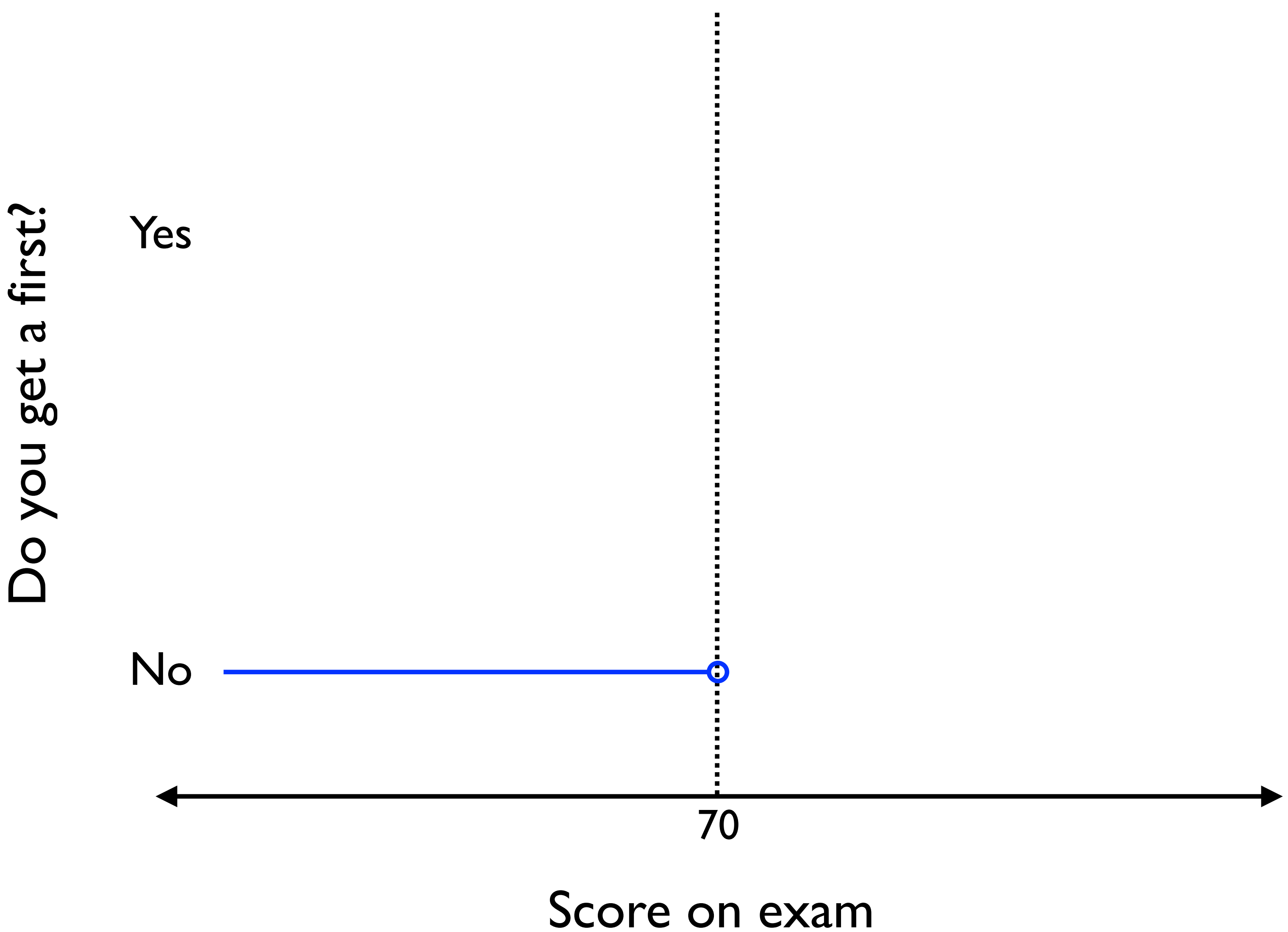

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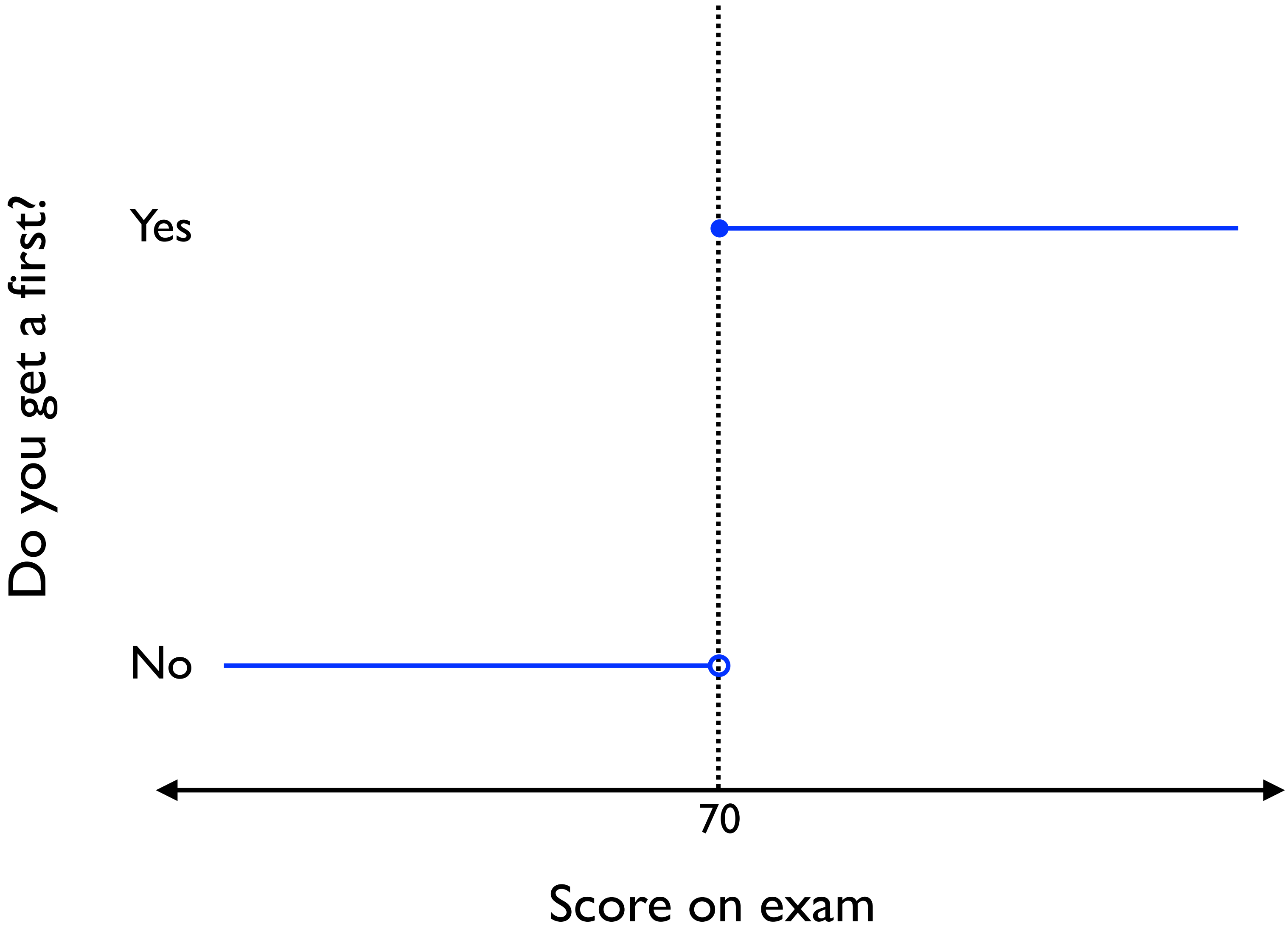


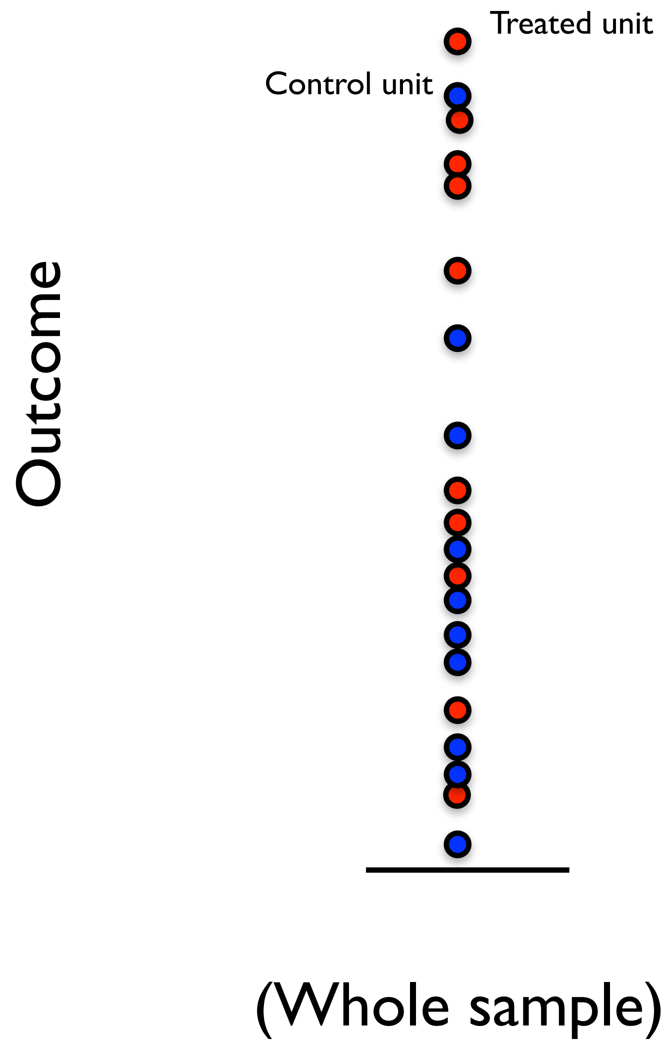
Plan

- Quick intuition (already done)
- Understanding the continuity assumption
- Examples
- Some more general evidence on RD validity
- Some guidance on estimation

Review: causal inference as missing data problem

Unit	Y_i	D_i	Y_{1i}	Y_{0i}
1	3	1	3	?
2	1	1	1	?
3	0	0	?	0
4	1	0	?	1
…	…	…	…	…

Estimating treatment effects in the whole sample



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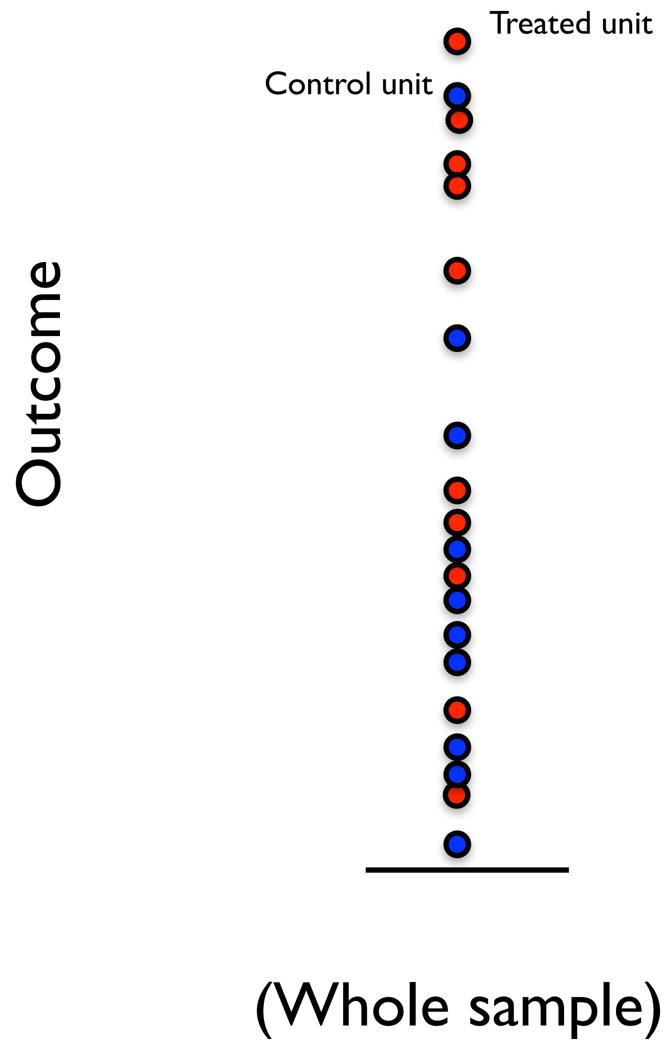

Recall ATT is

$E[Y_1|D_i=1] - E[Y_0|D_i=1]$.

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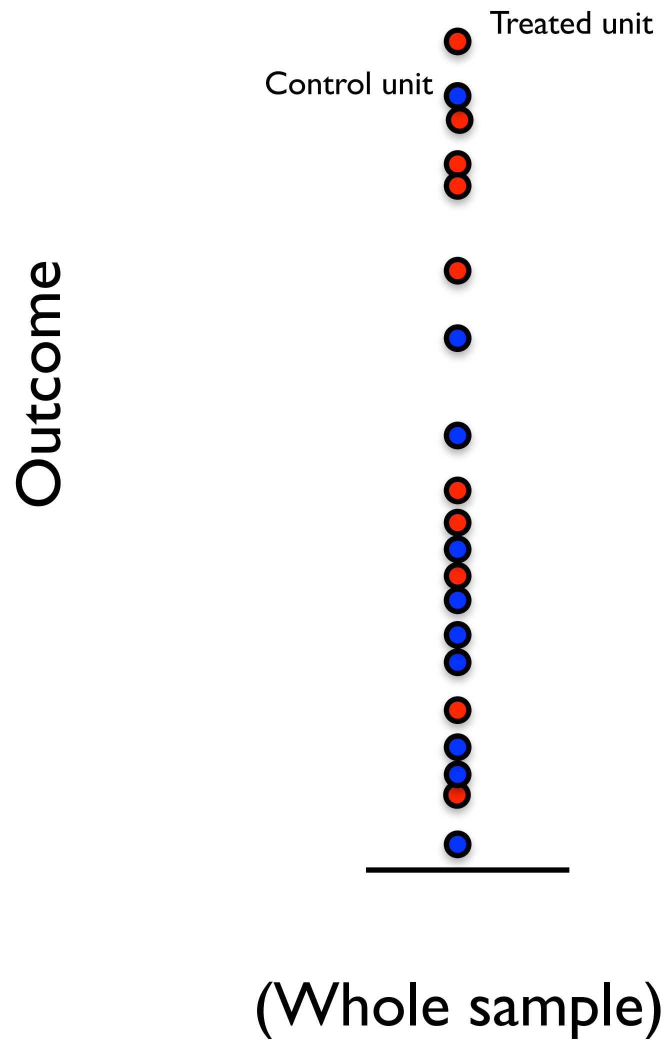

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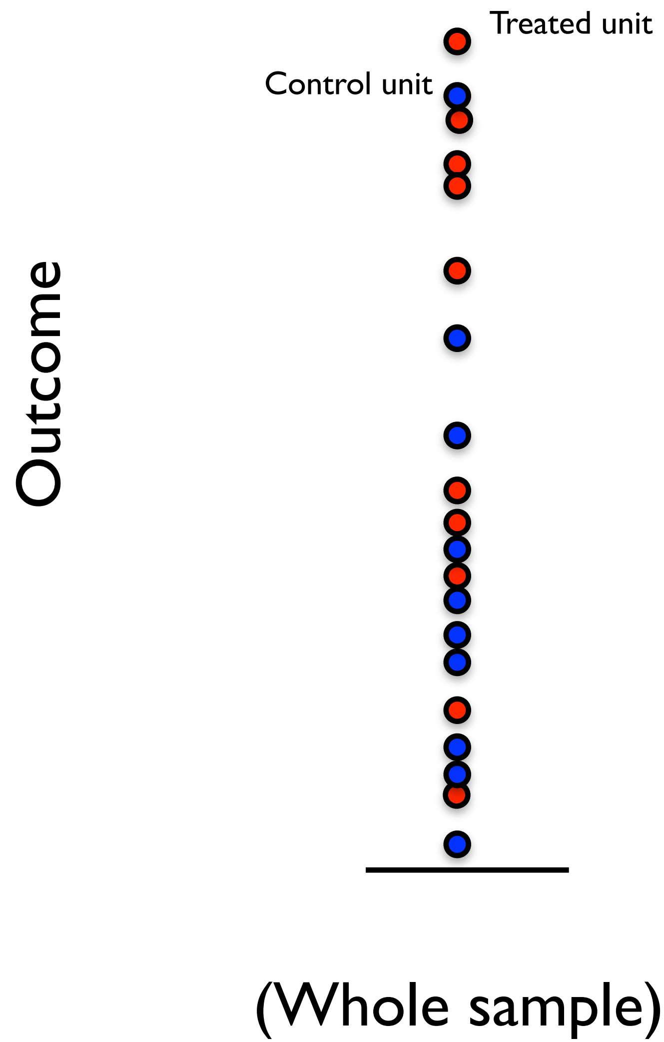

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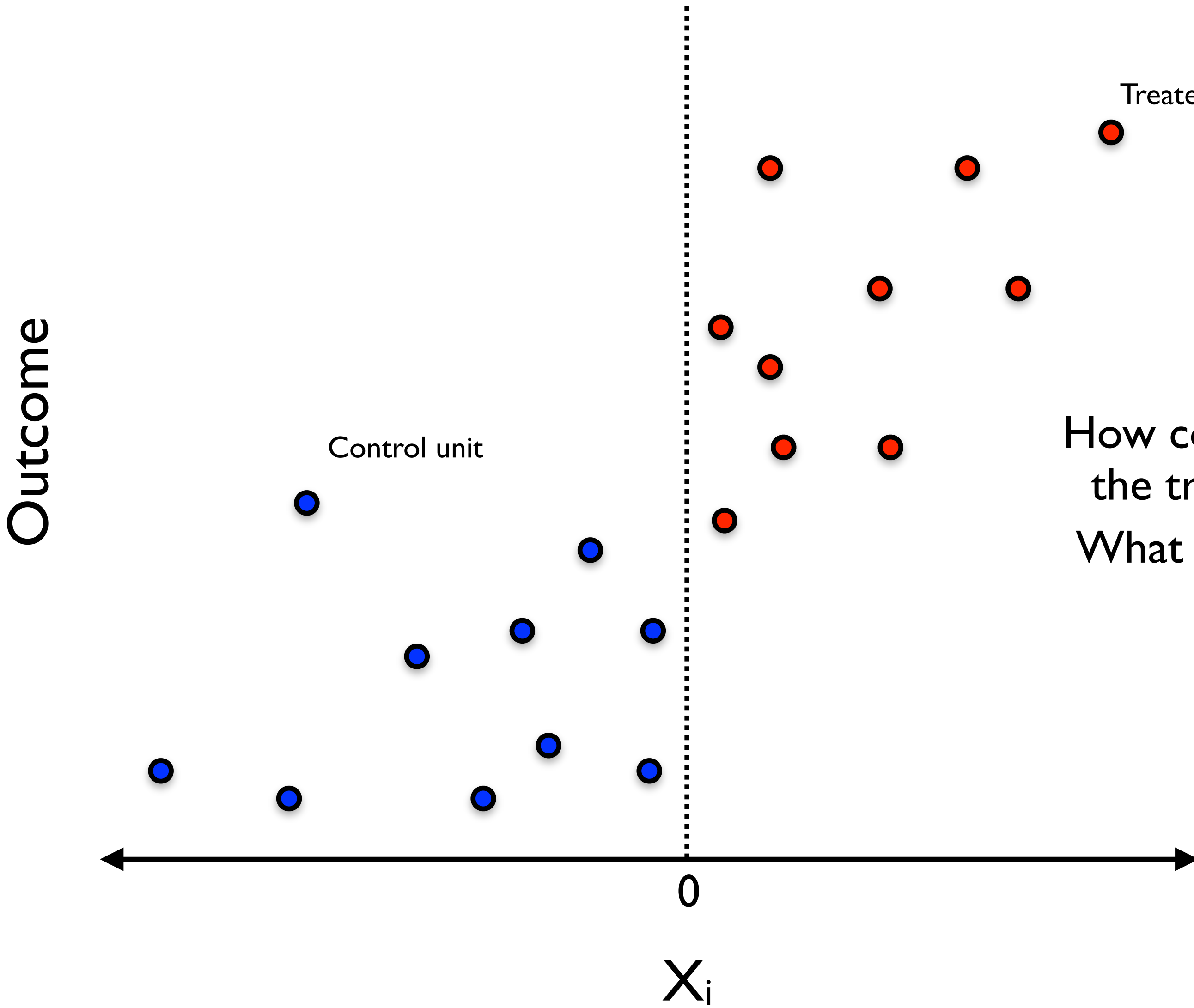
Under what conditions does this give an unbiased estimate?

What if treatment assignment depends on a cutoff value of X_i?

Assignment mechanism: $D_i = 1$ iff $X_i \geq 0$

Unit	Y_i	D_i	Y_{1i}	Y_{0i}	X_i
1	3	1	3	?	0.3
2	1	1	1	?	0.7
3	0	0	?	0	-1.2
4	1	0	?	1	-0.4
…	…	…	…	…	

Estimating treatment effects when treatment depends on a discontinuity



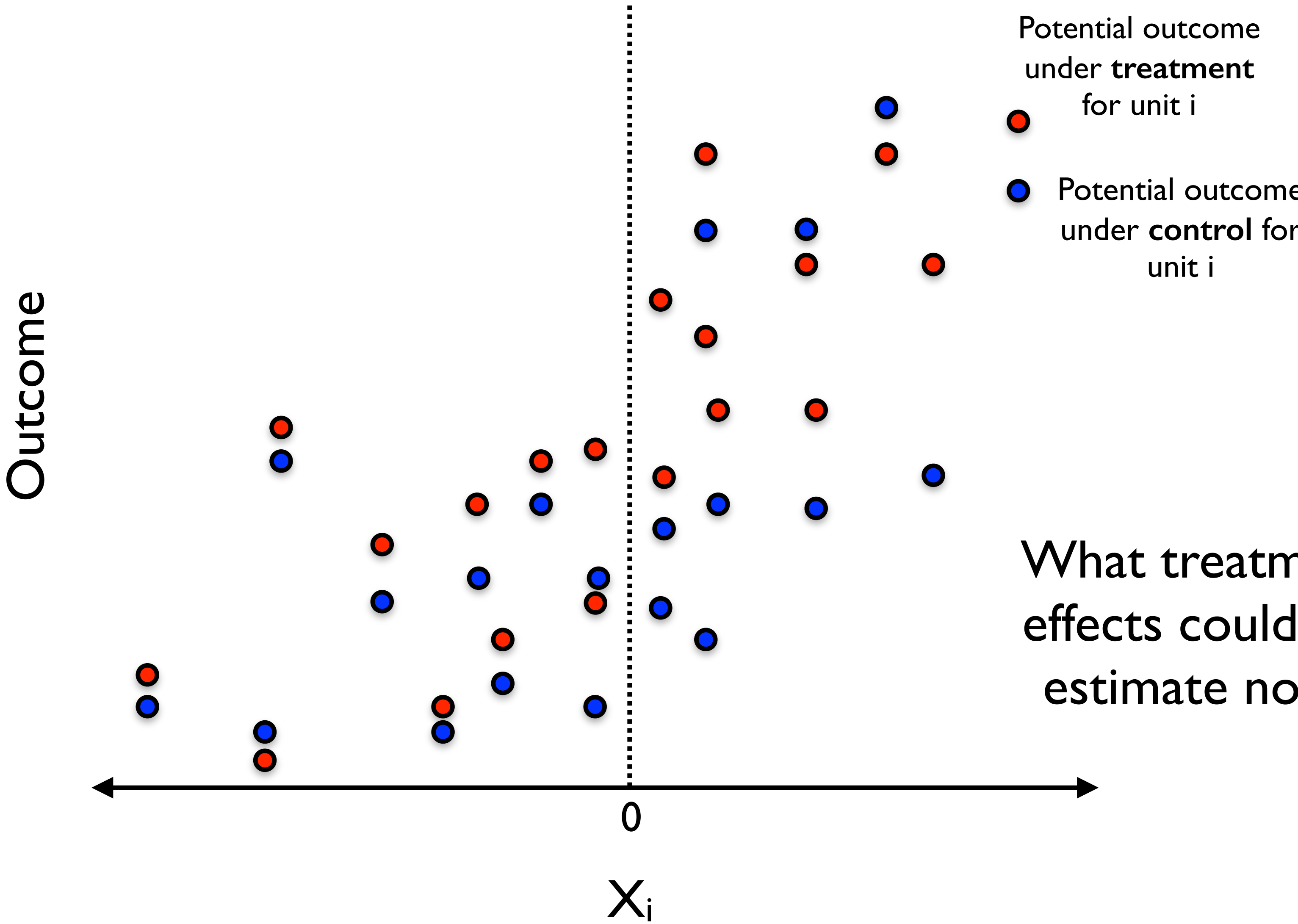
How could we estimate the treatment effect?

What assumptions are we using?

Suppose the FPOCI is overcome (rejoice!)

Unit	Y_i	D_i	Y_{1i}	Y_{0i}	X_i
1	3	1	3	1.4	0.3
2	1	1	1	0.8	0.7
3	0	0	1.3	0	-1.2
4	1	0	1.1	1	-0.4
...	...	...	...	...	

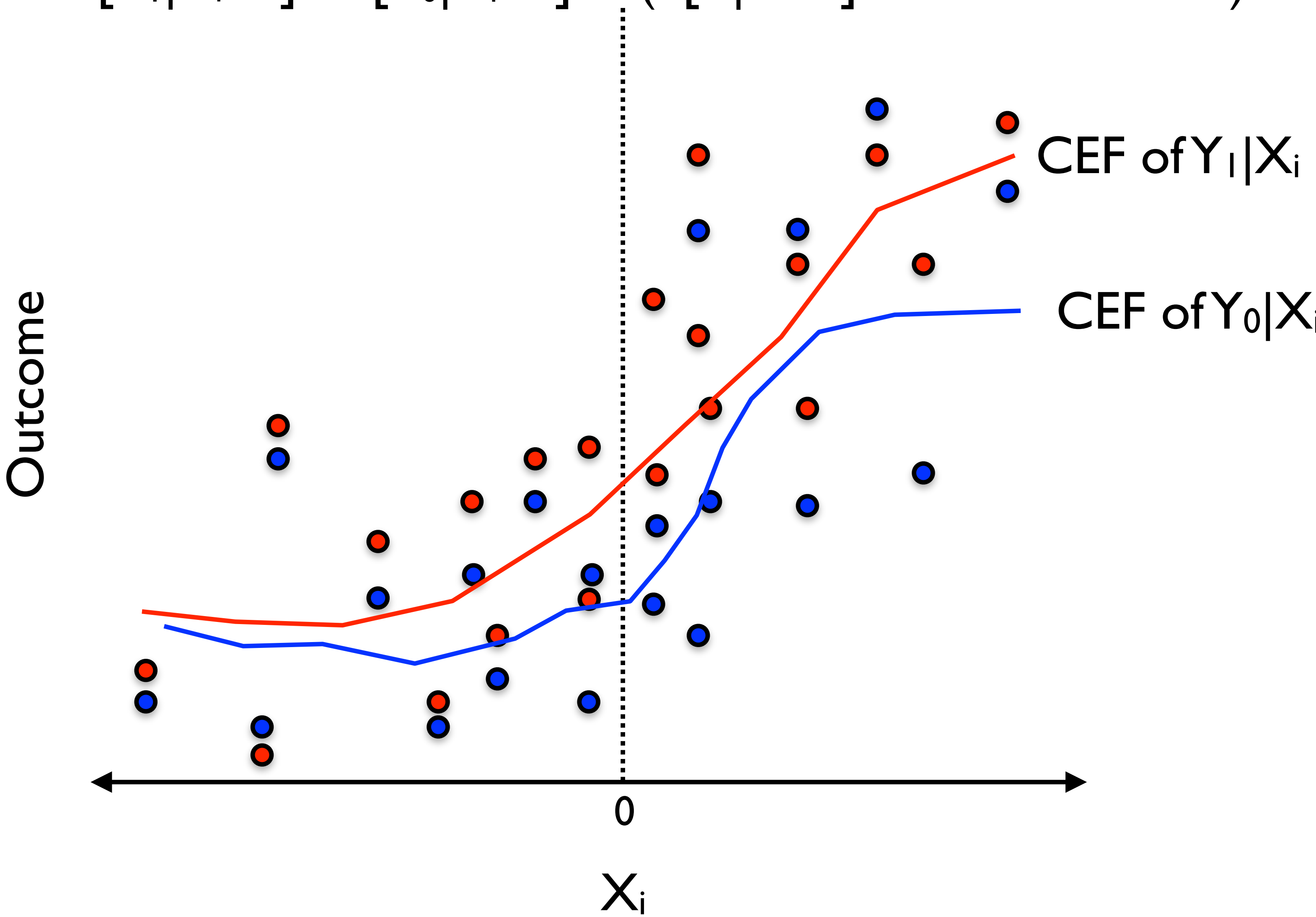
Estimating treatment effects when both potential outcomes are observed



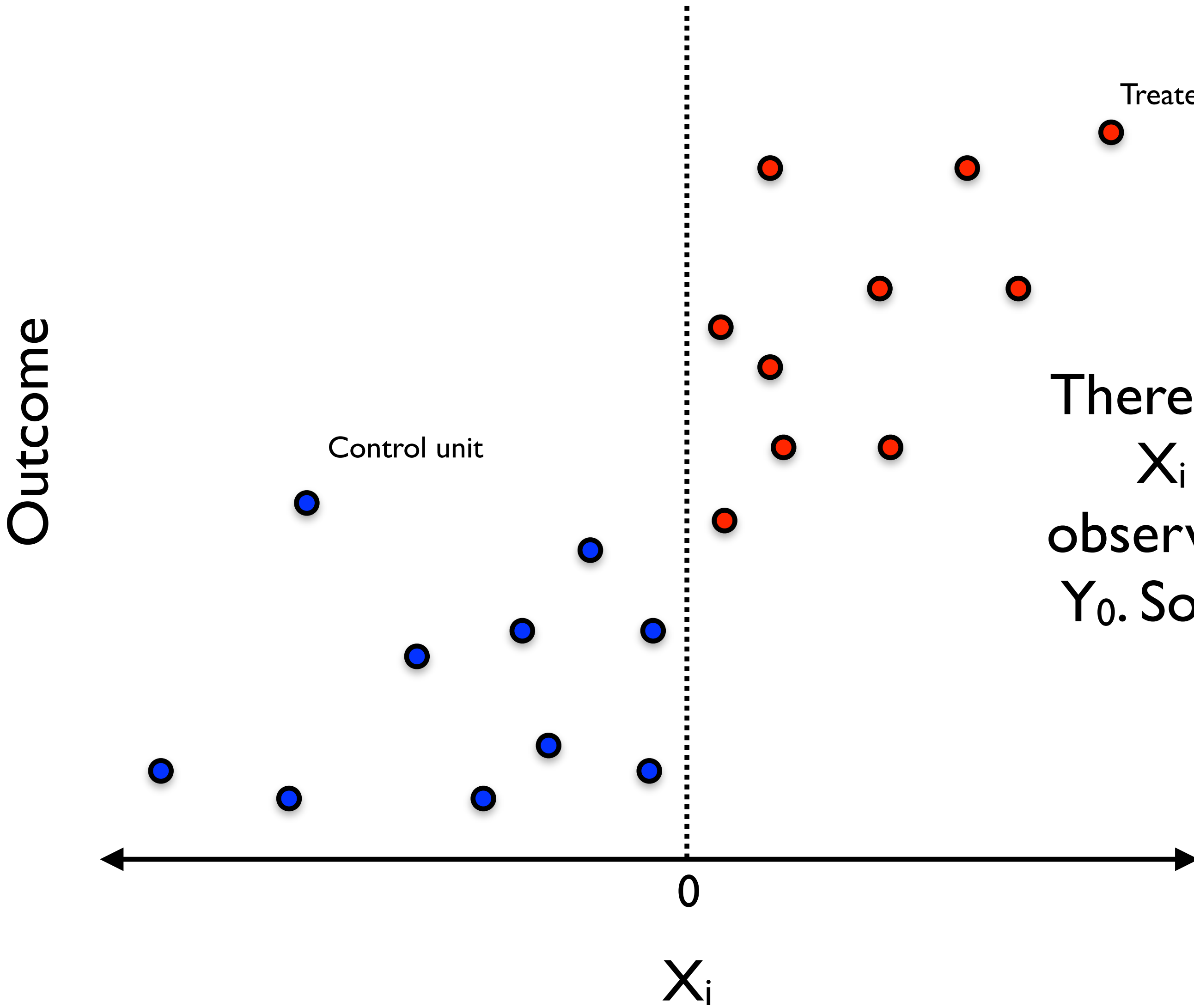
What treatment effects could we estimate now?

Here's one: Local average treatment effect (LATE)

LATE: $E[Y_1|X_i=x] - E[Y_0|X_i=x]$. ($E[Y|X=x]$ is the "CEF at x")



Back to reality: FPOCI



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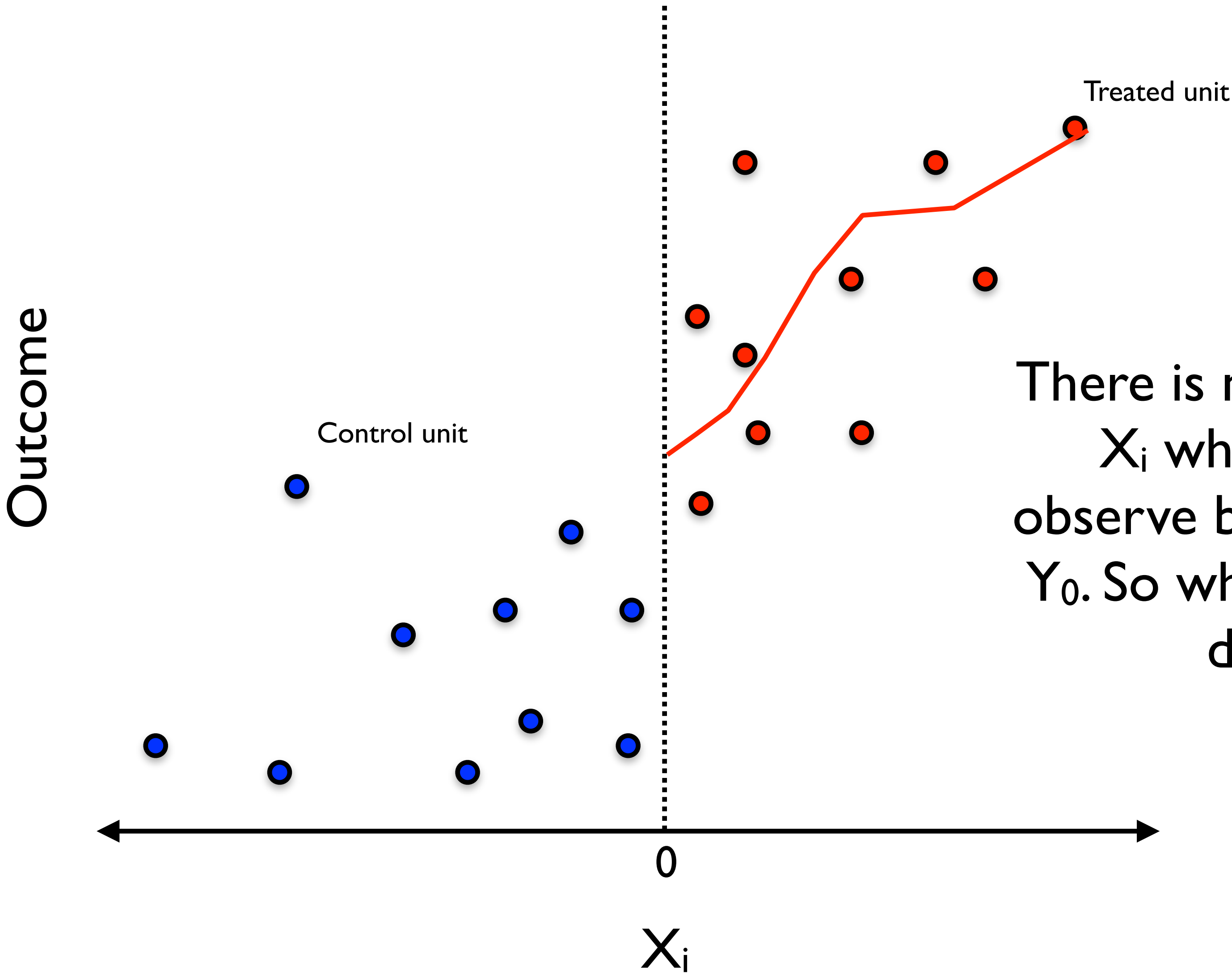

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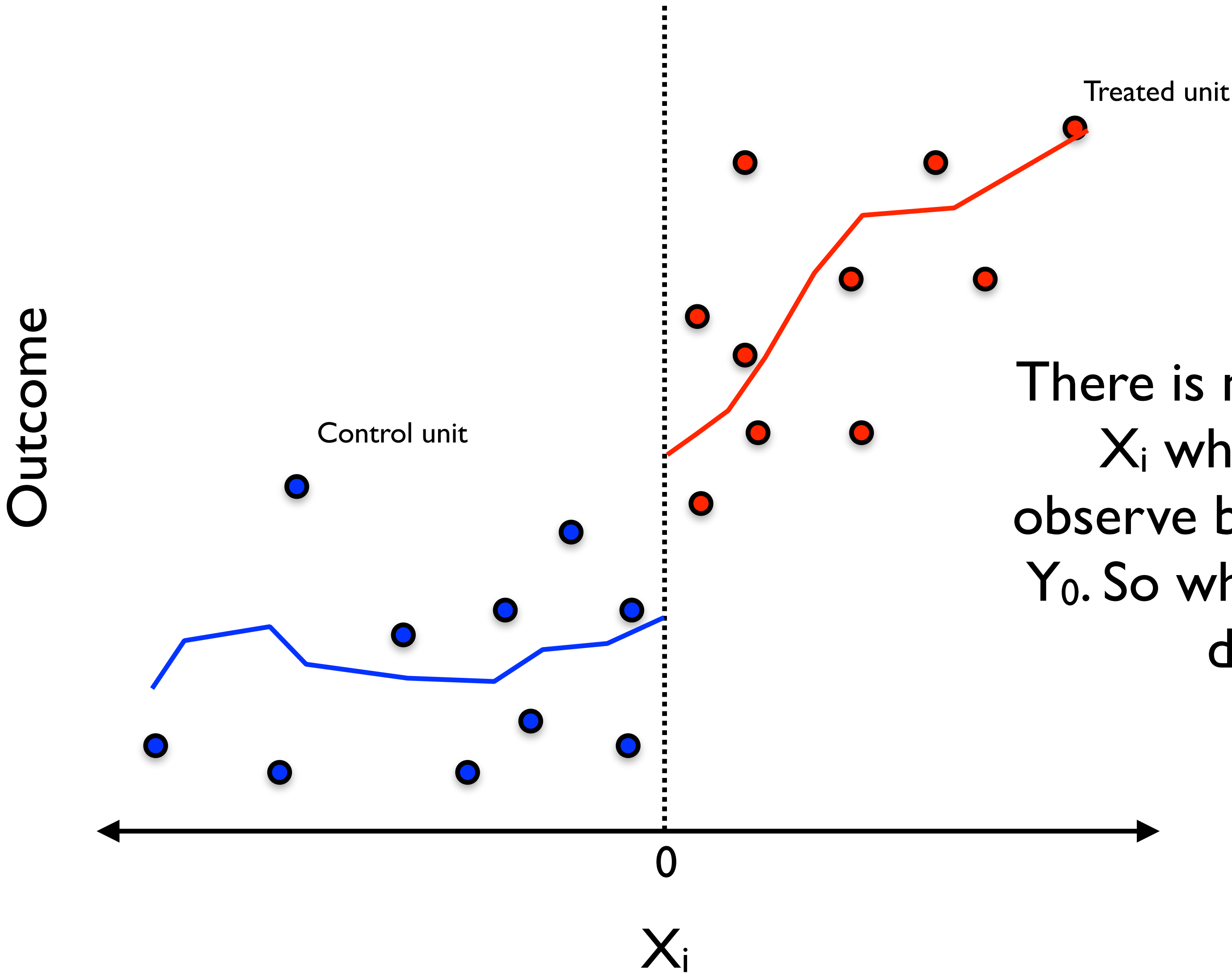

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$$E[Y_1|X_i = 0] = \lim_{x \to 0^+} E[Y_1|X_i = x]$$

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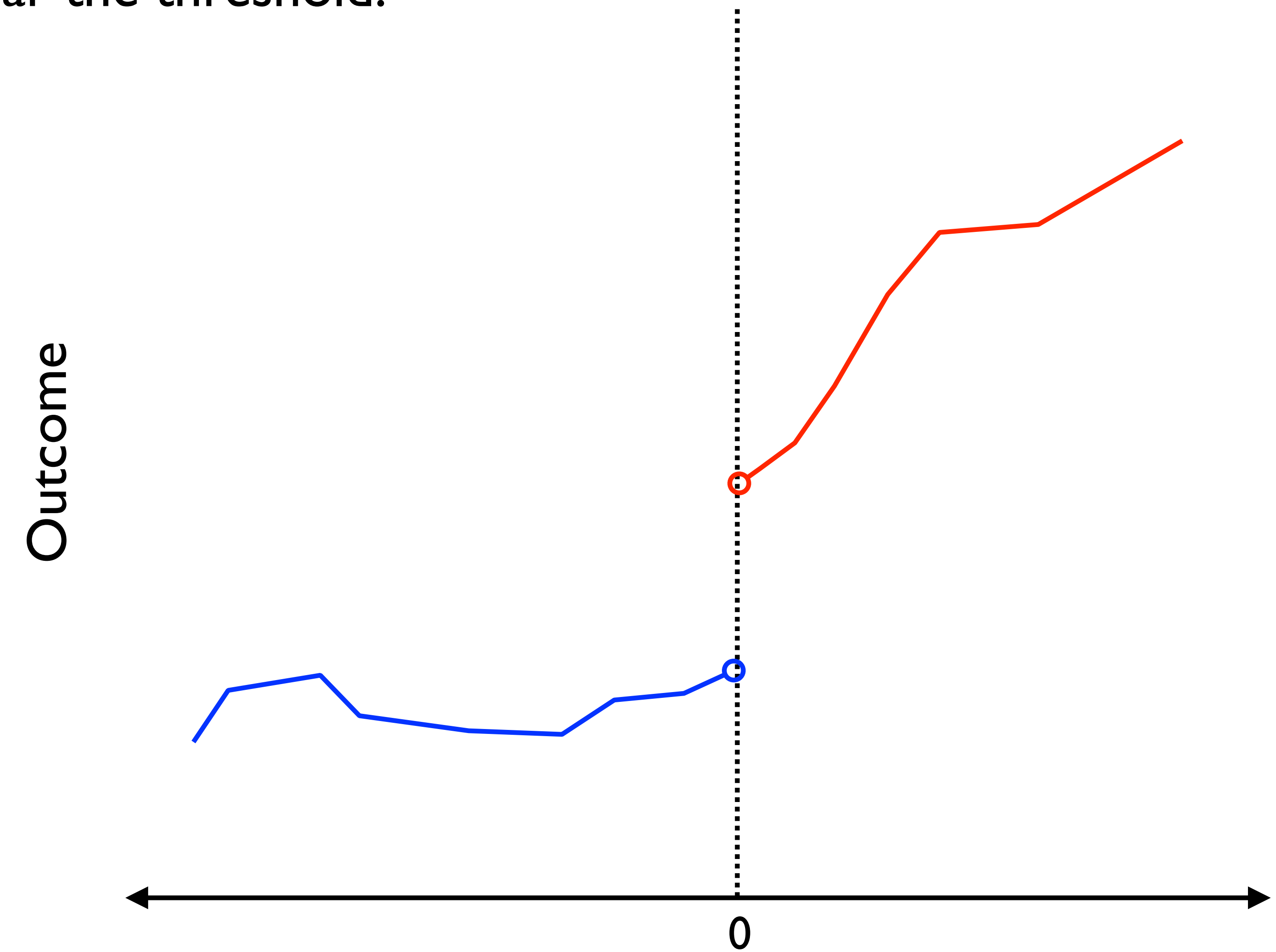
When would these assumptions be valid?

When can we extrapolate to the threshold?

Given infinite data, the only requirement is **continuity of the CEFs** near the threshold.



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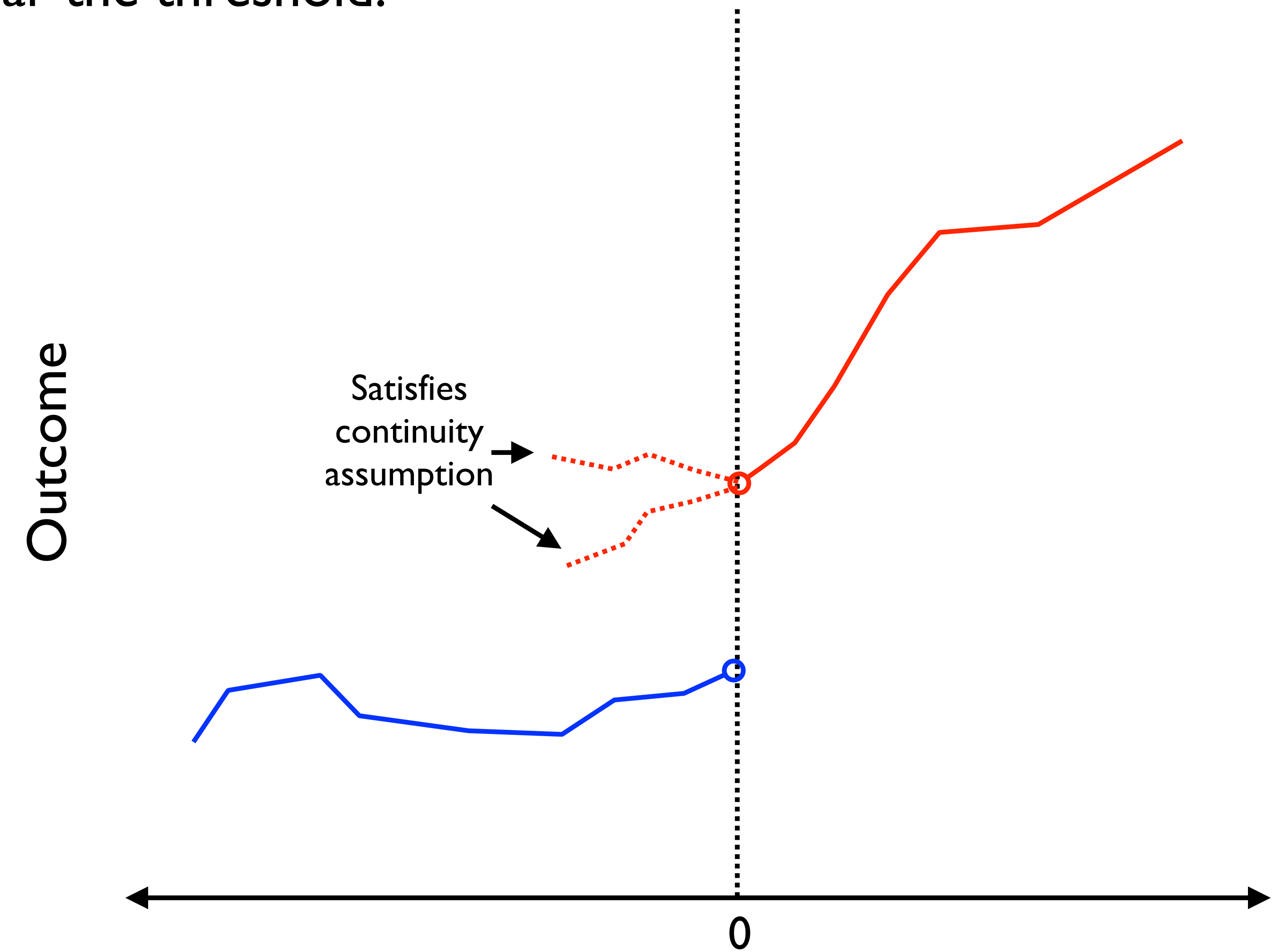

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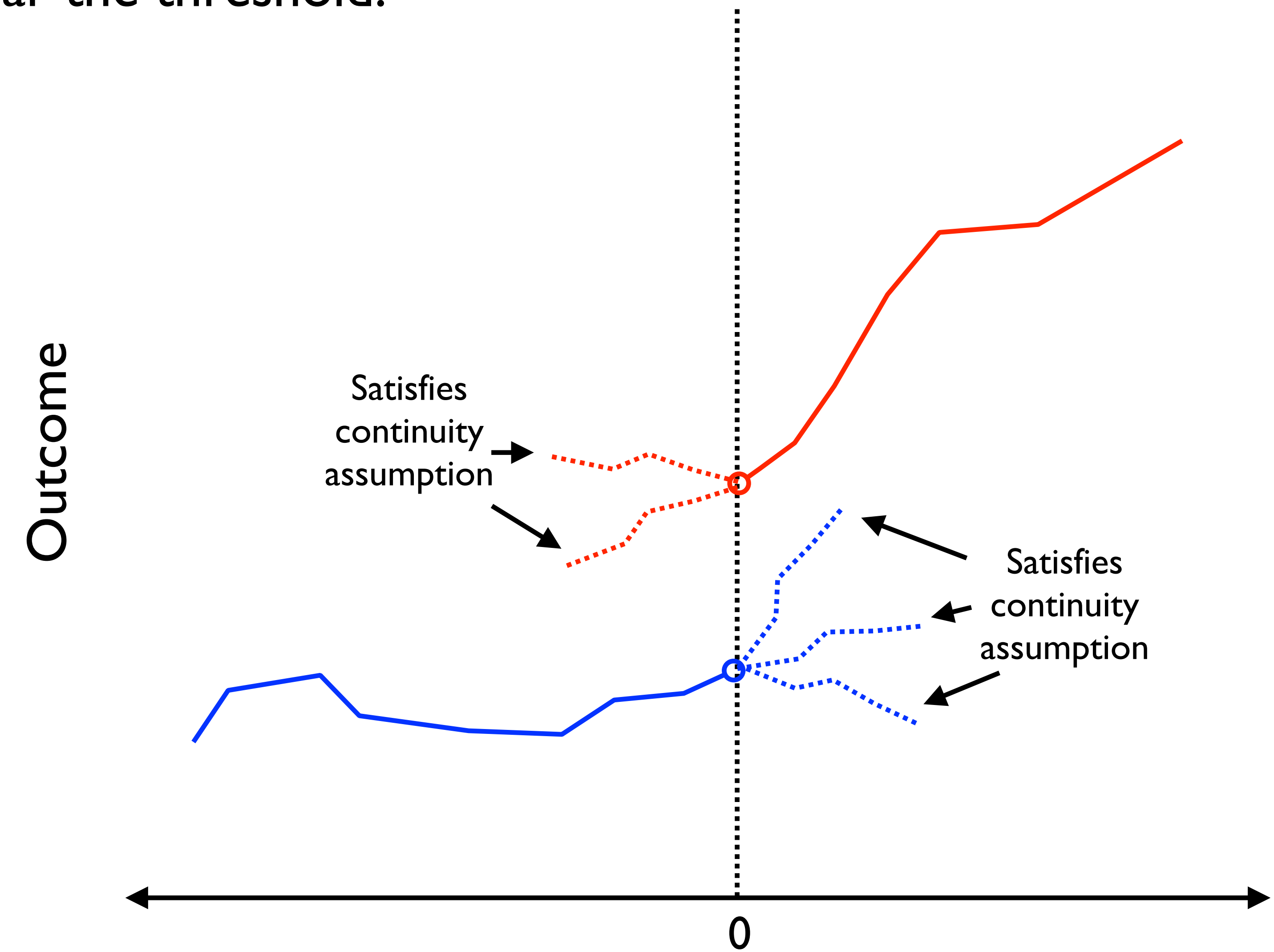

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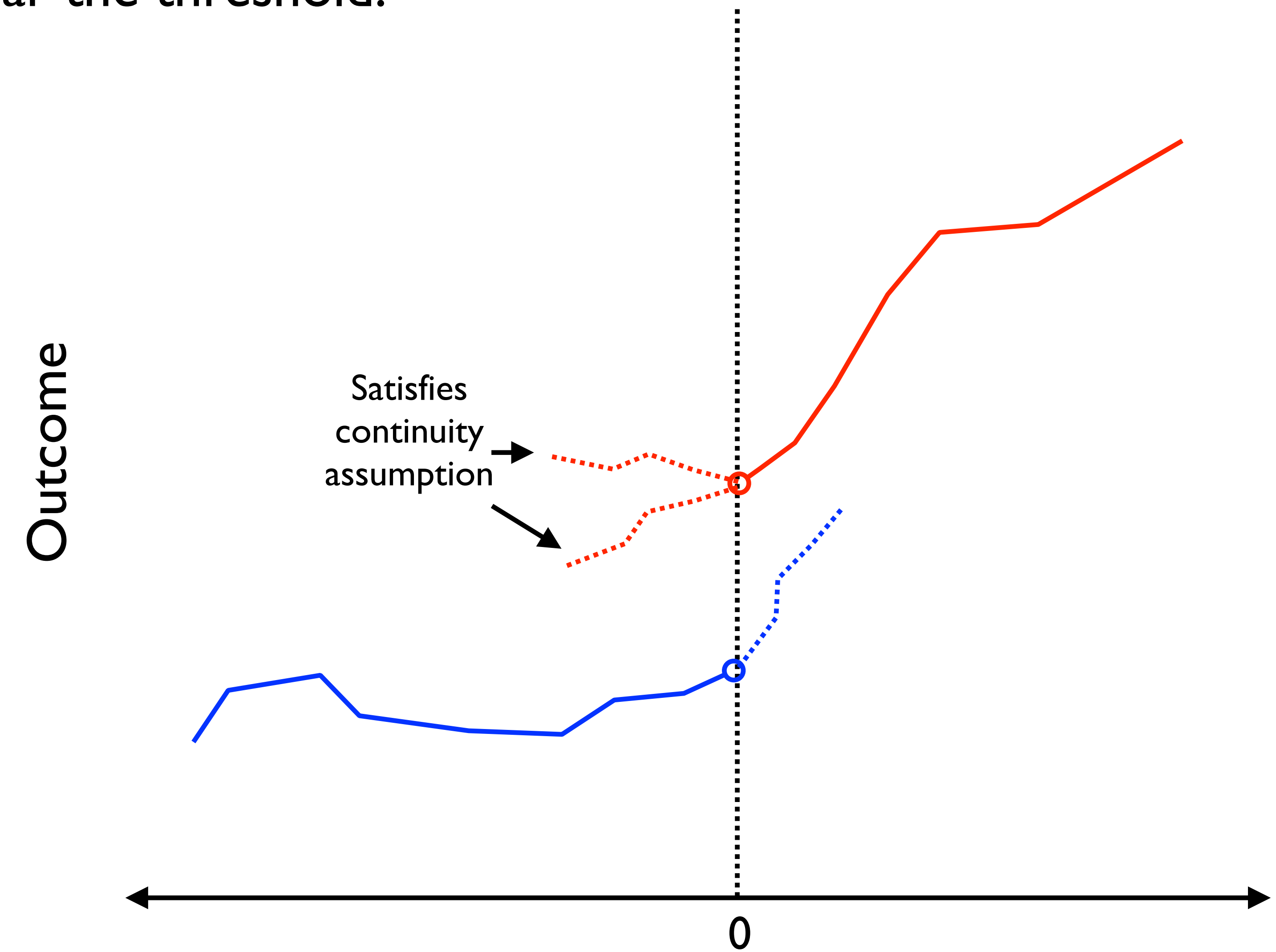

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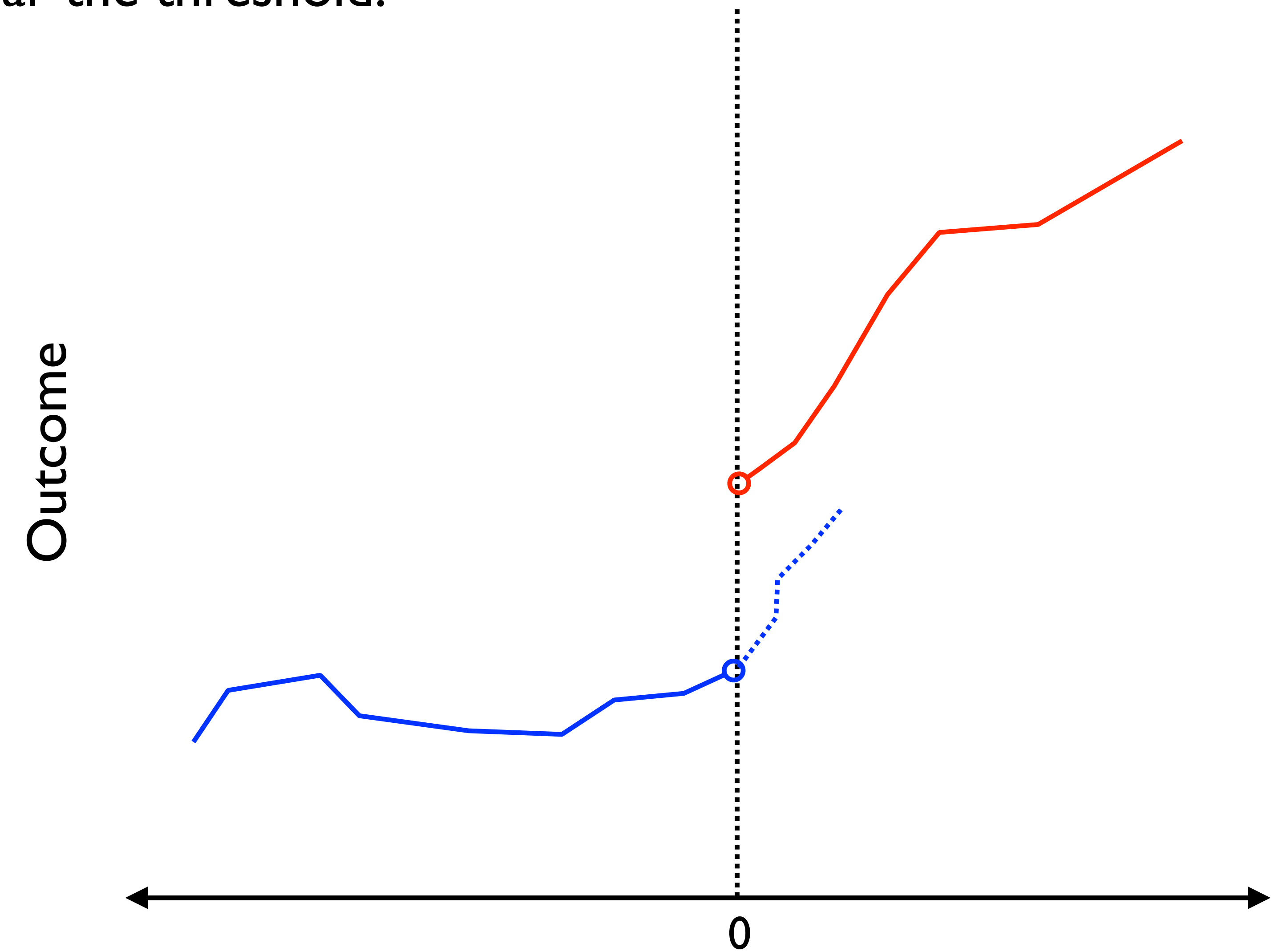

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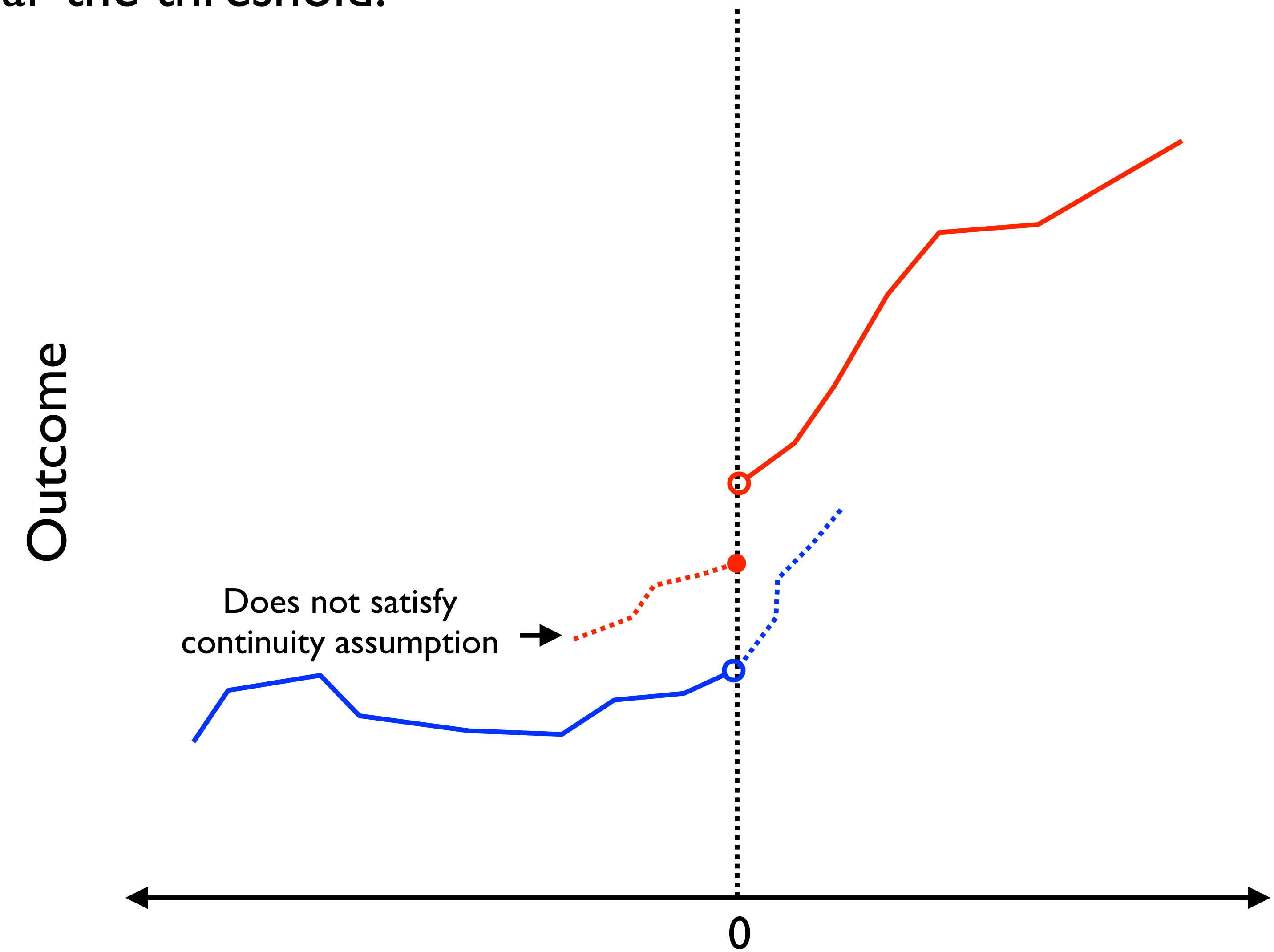

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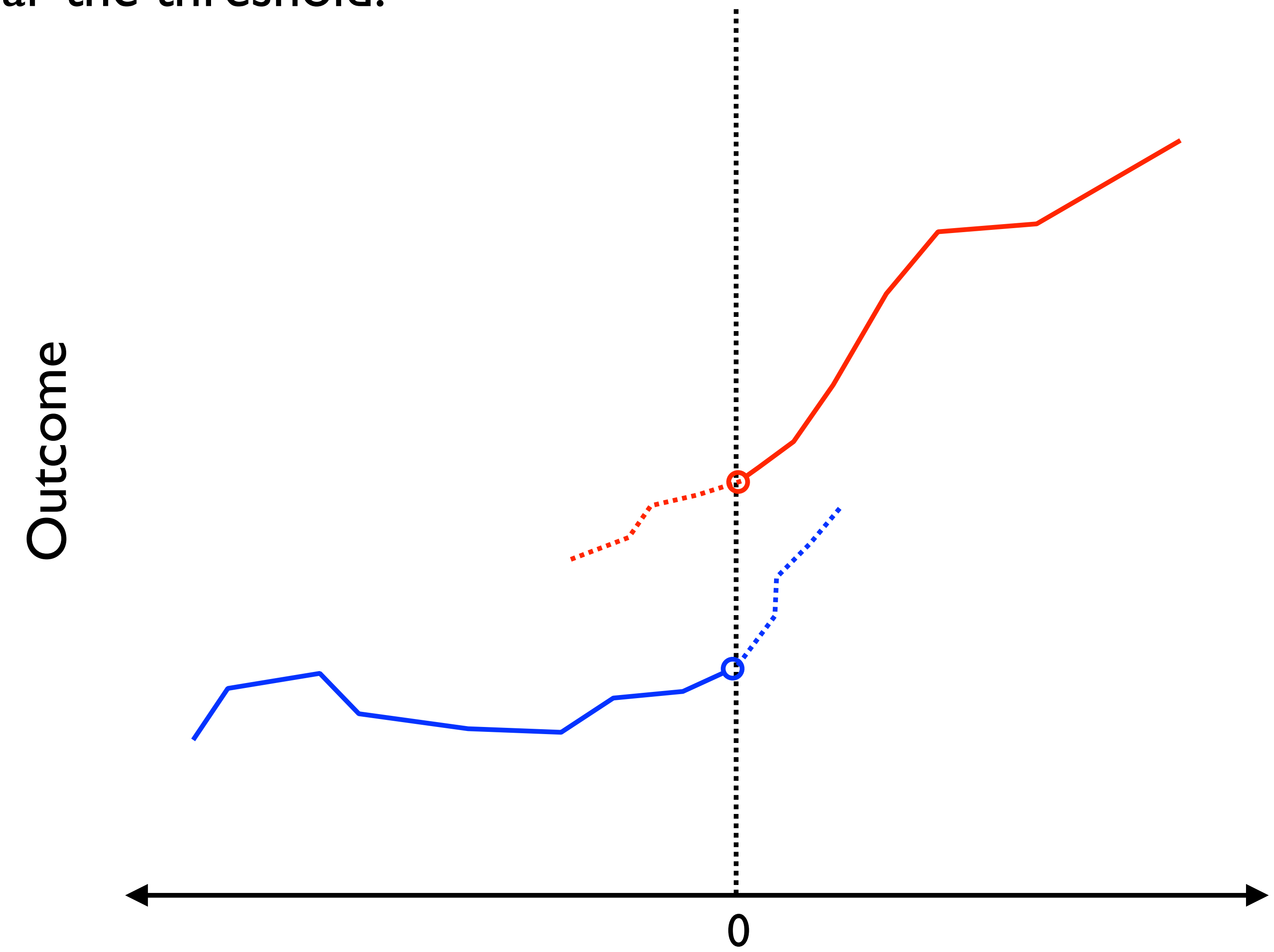

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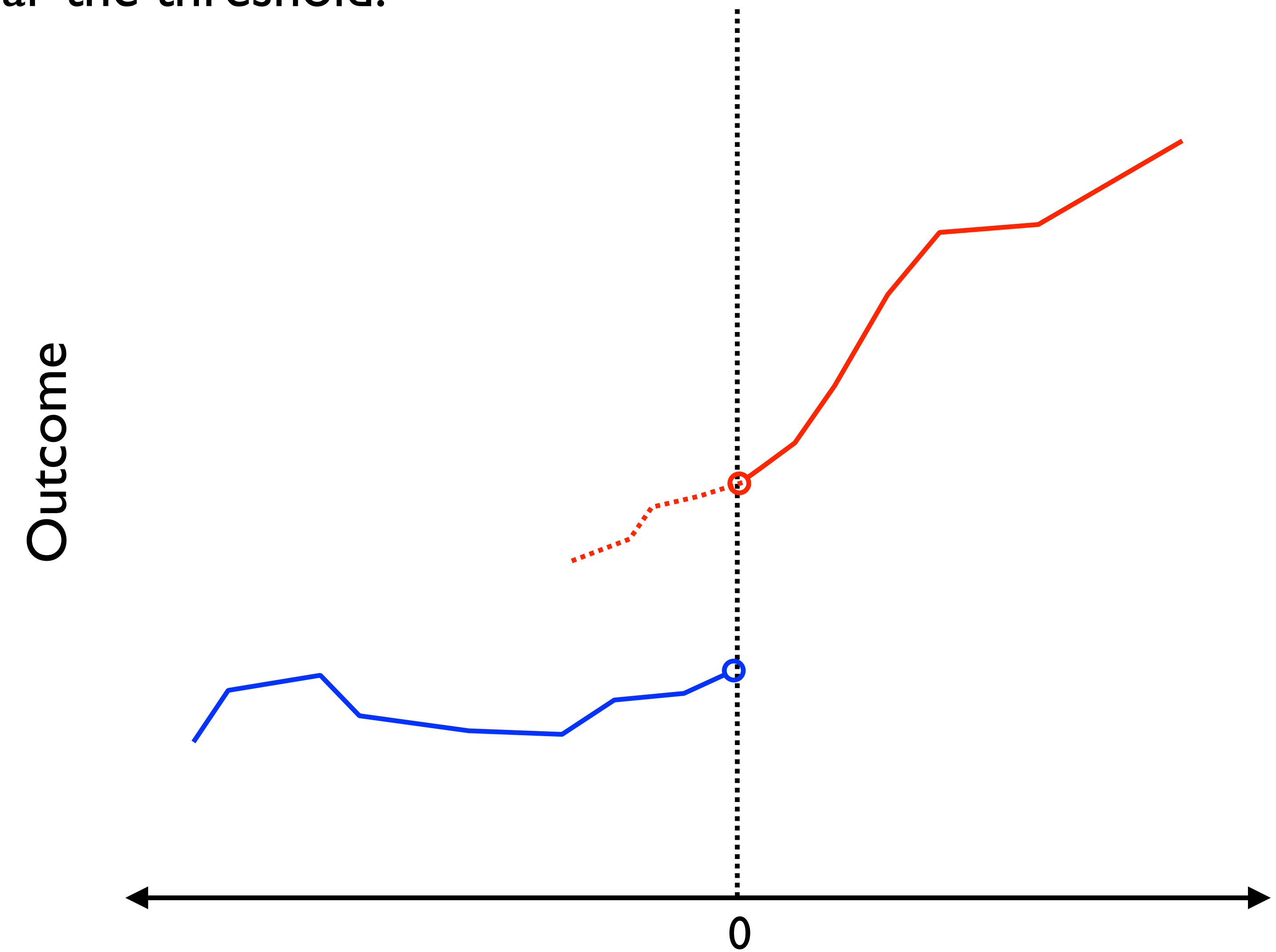

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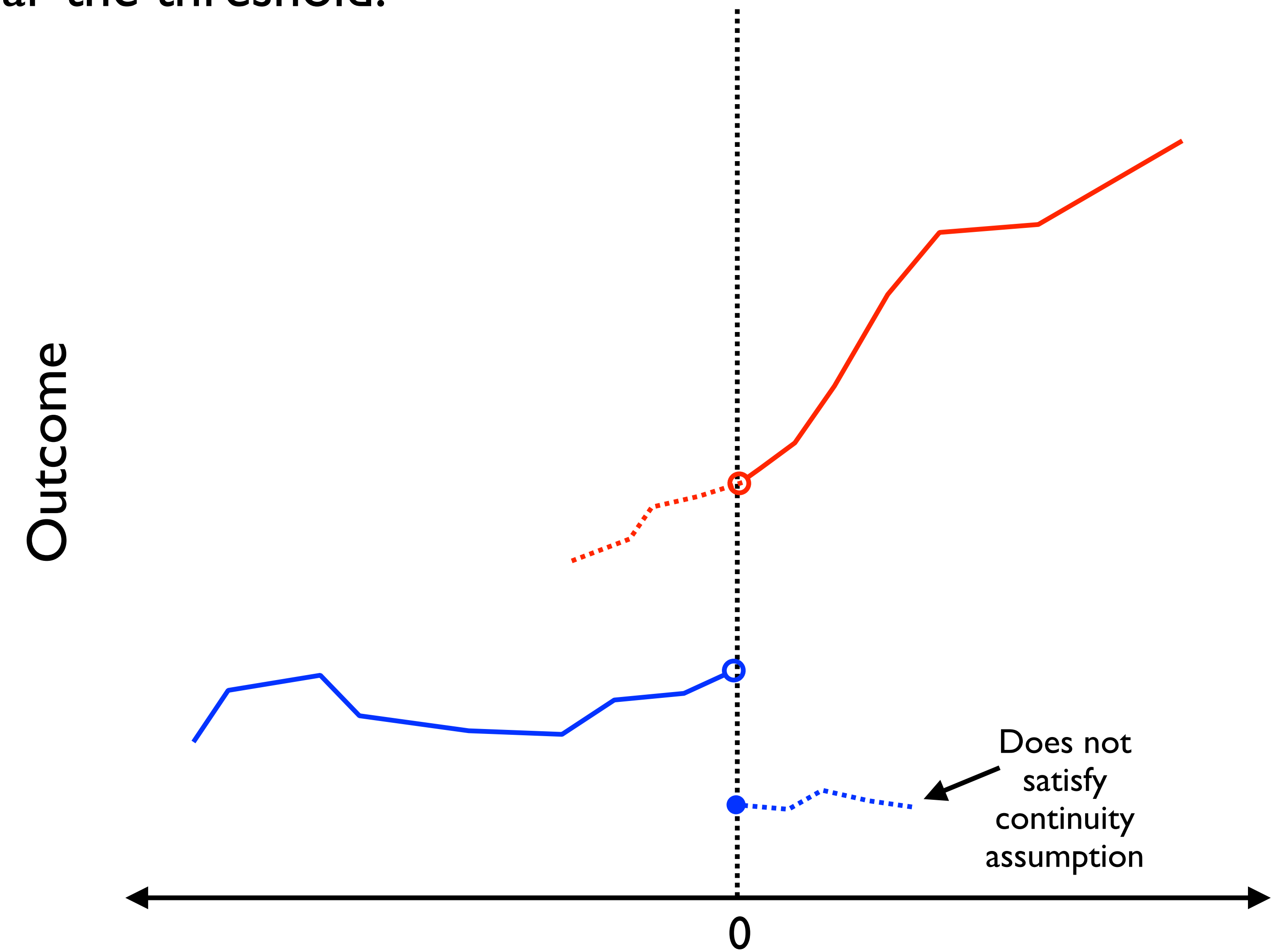
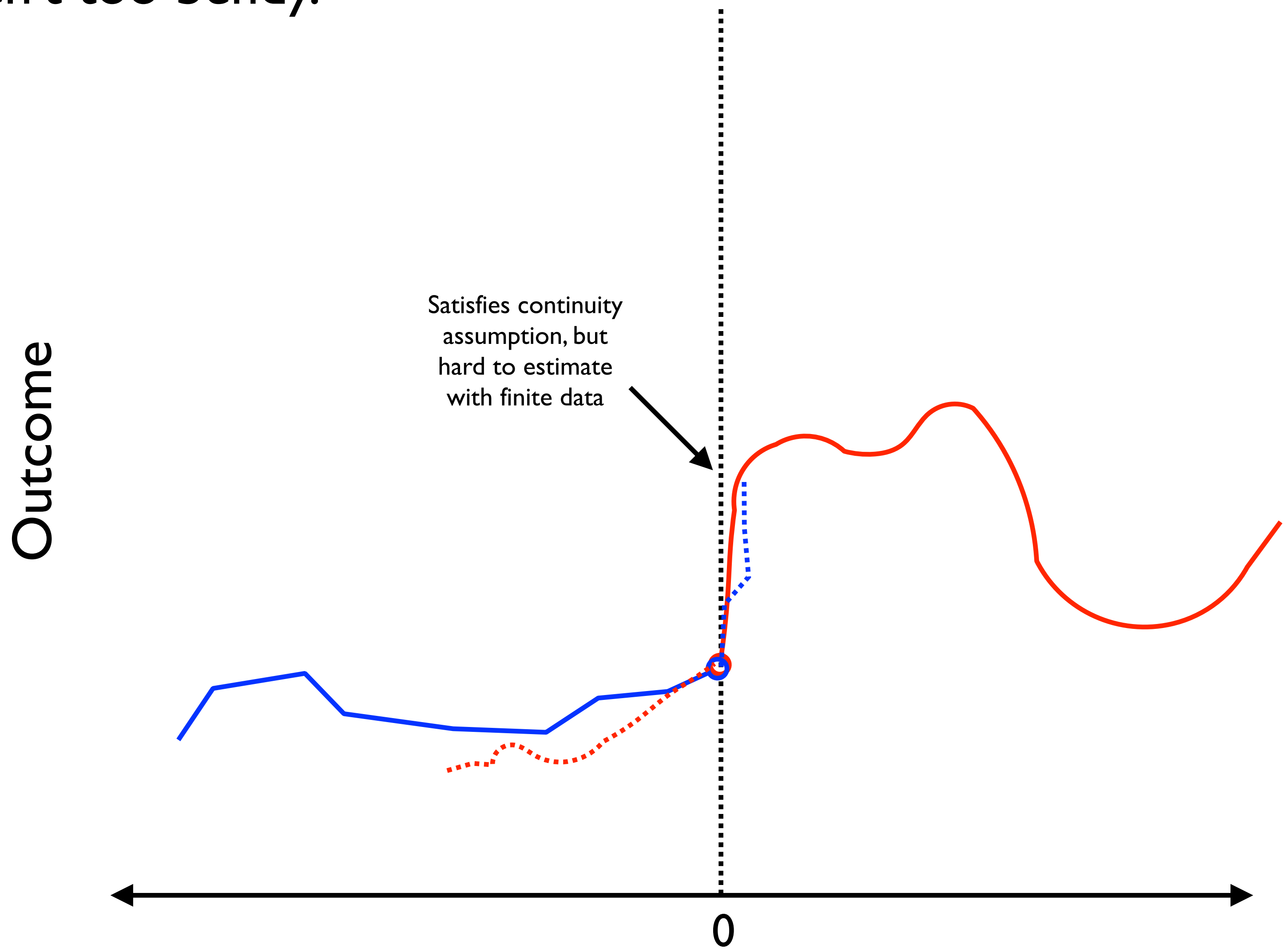


When can we extrapolate to the threshold? (2)

In practice, we also need either (a) a lot of data or (b) CEFs that aren't too bendy.



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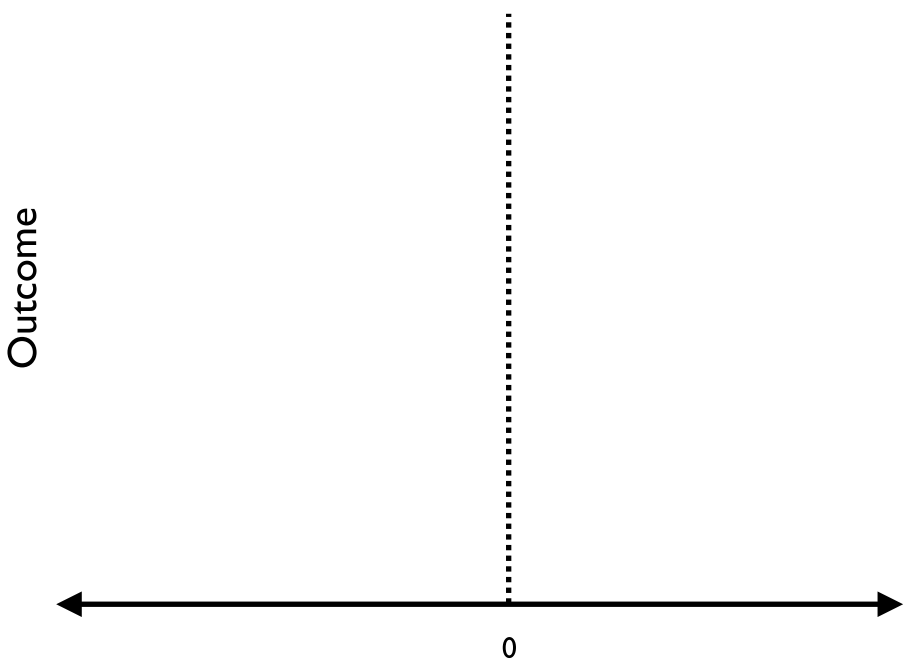

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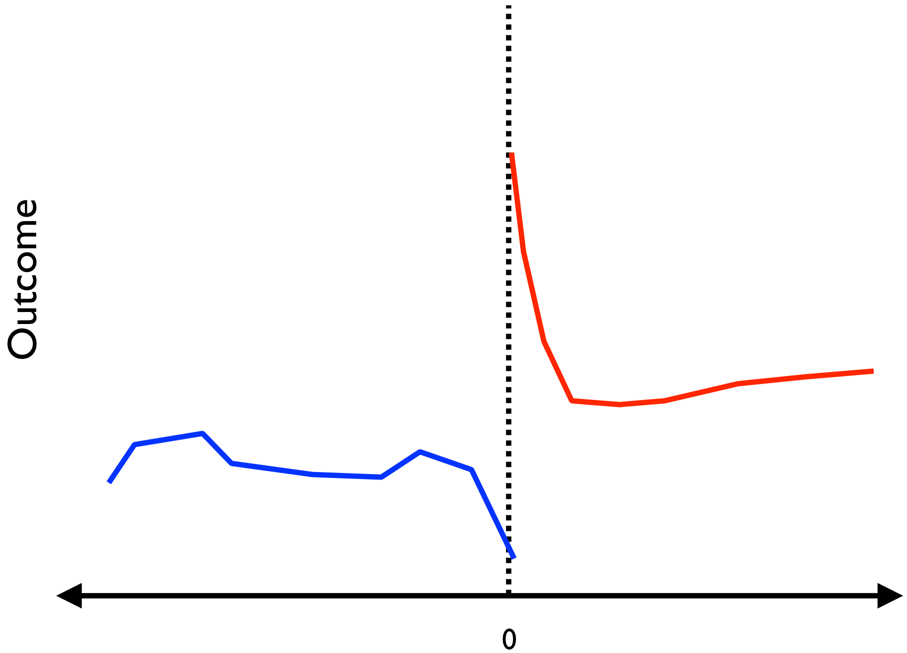

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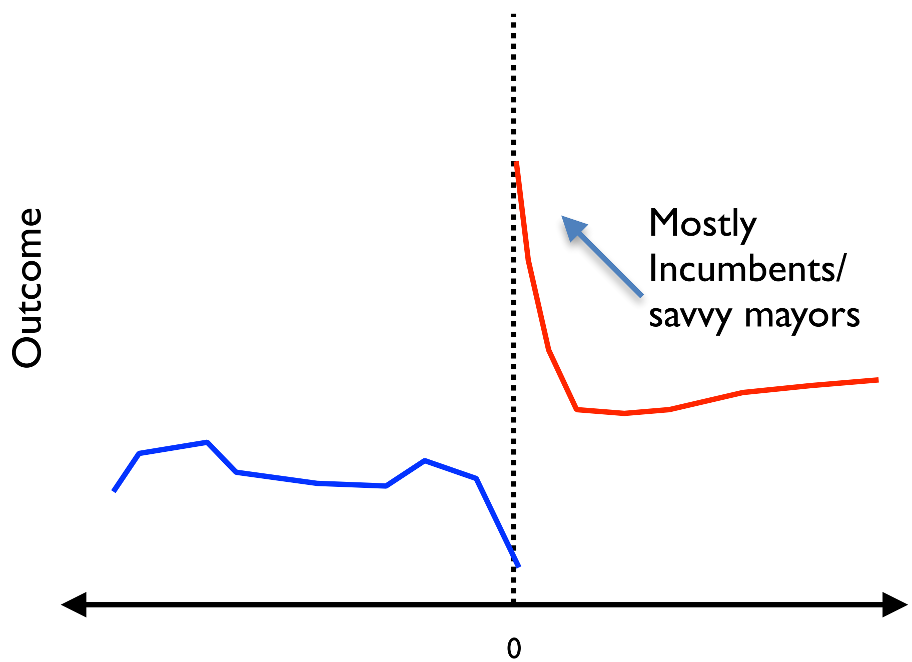

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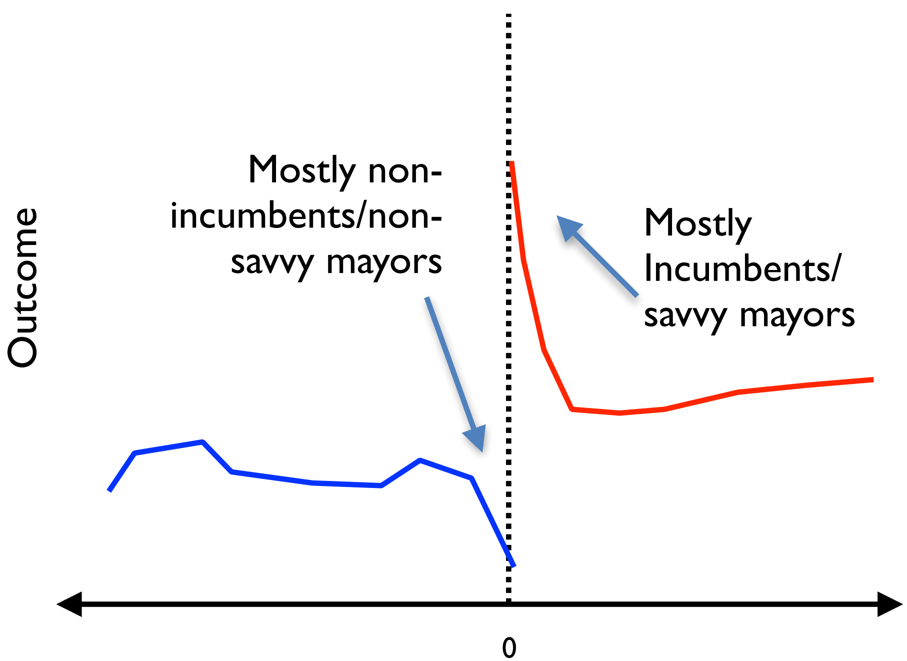

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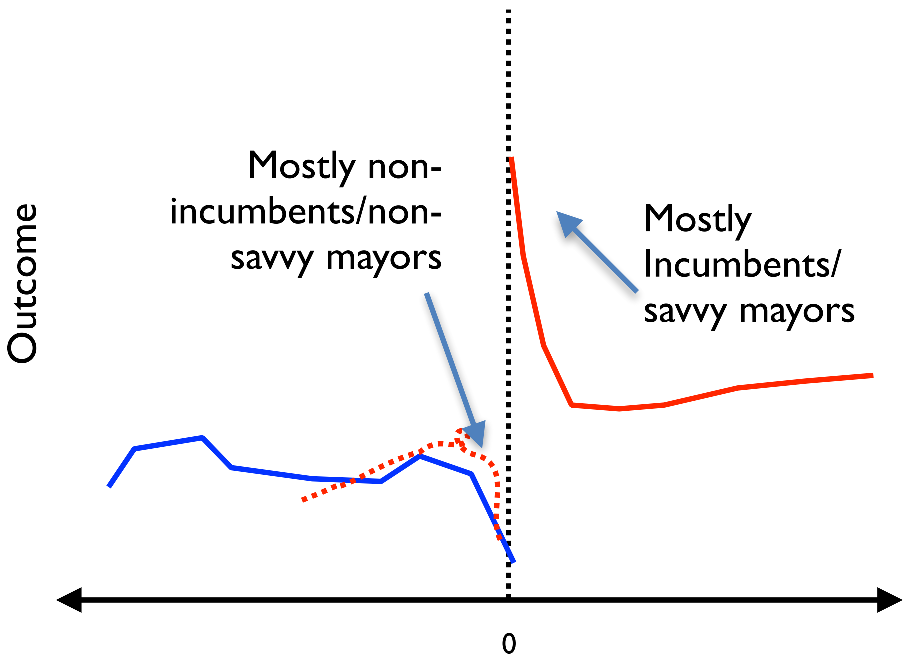

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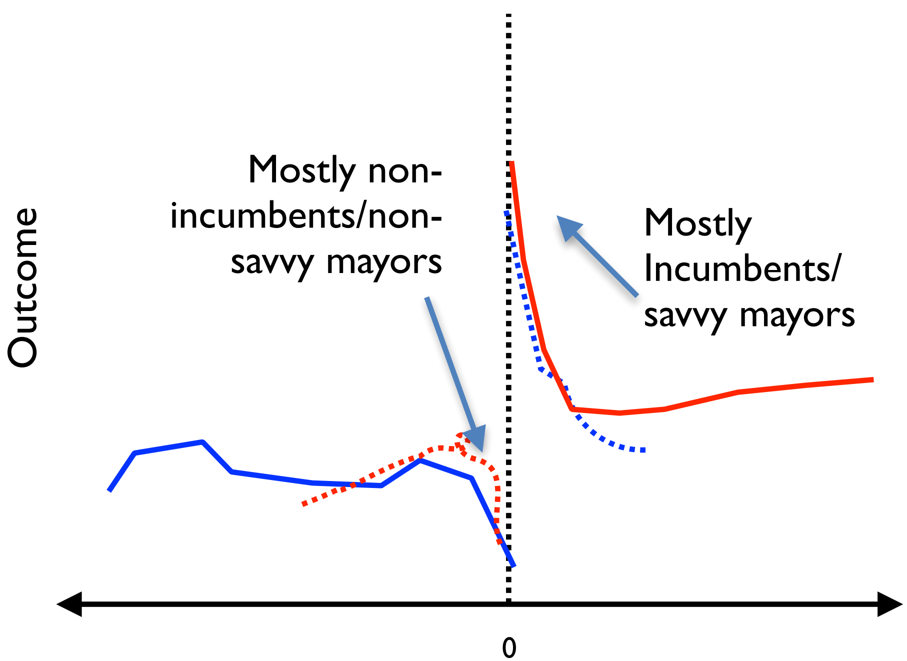

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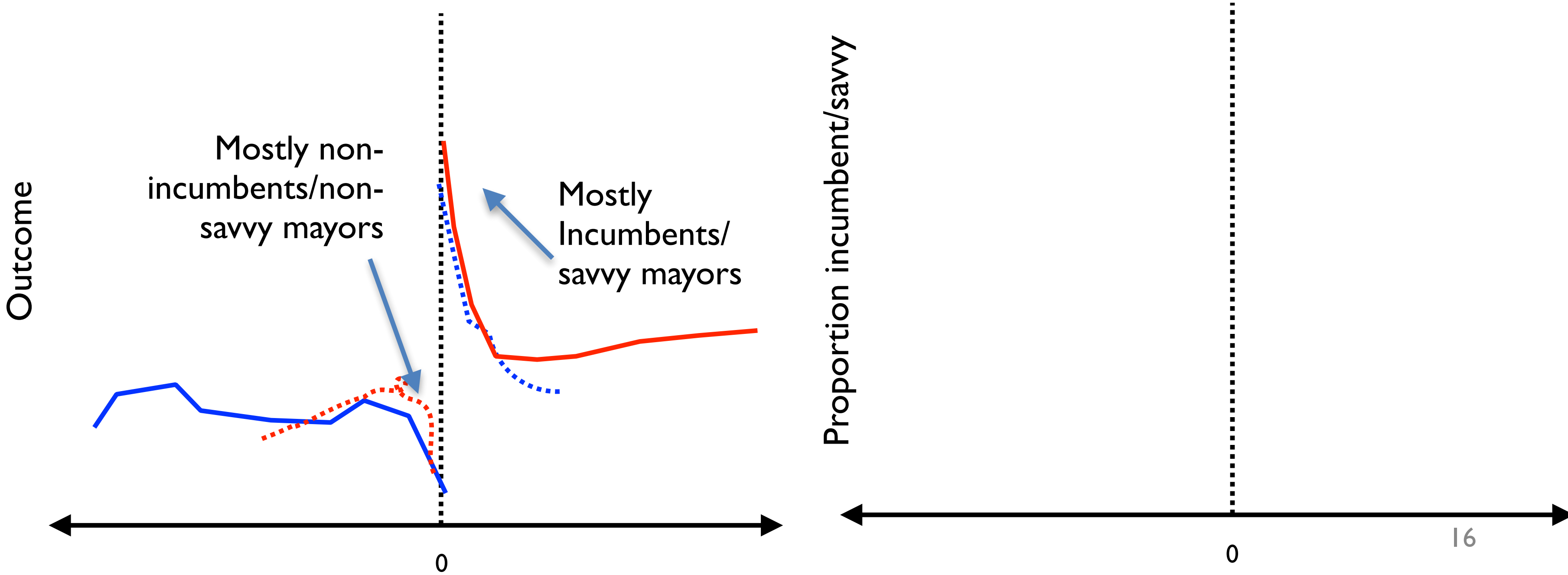

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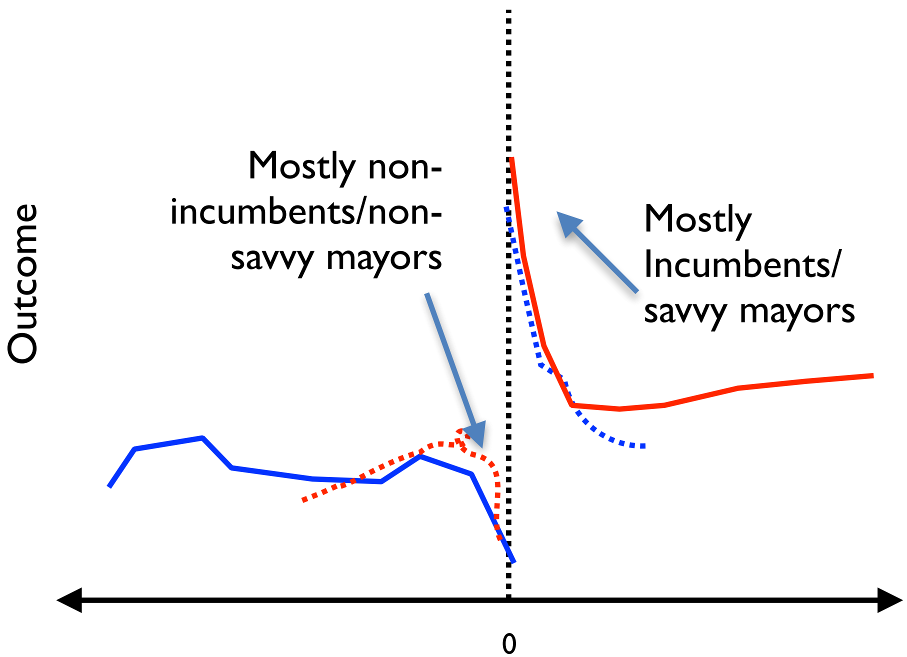

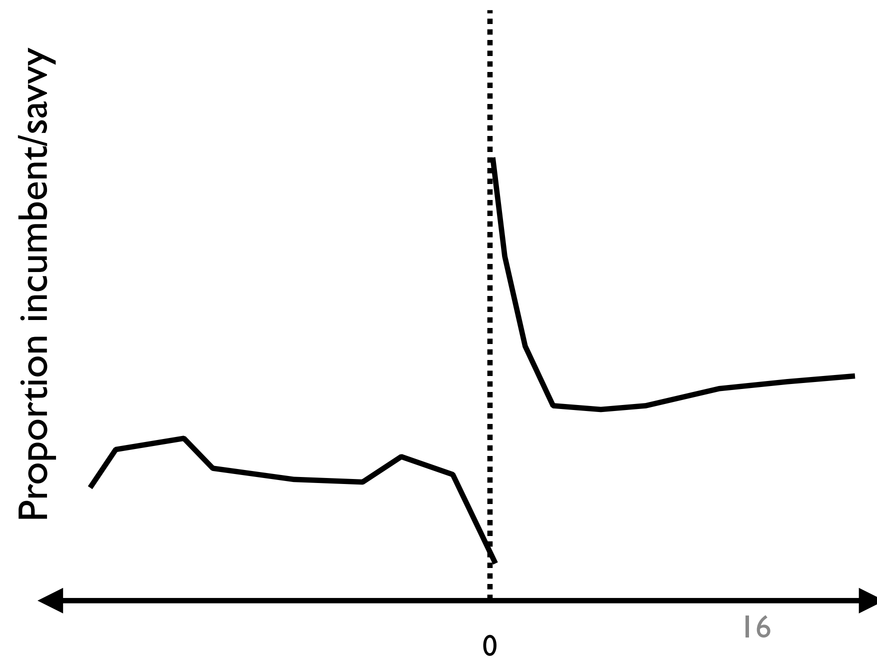

So how do we check for sorting?

- Is the density of the running variable continuous across the threshold? (McCrary 2008)
- Are covariates (e.g. incumbency status, mayor characteristics, lagged outcomes) continuous across the threshold?

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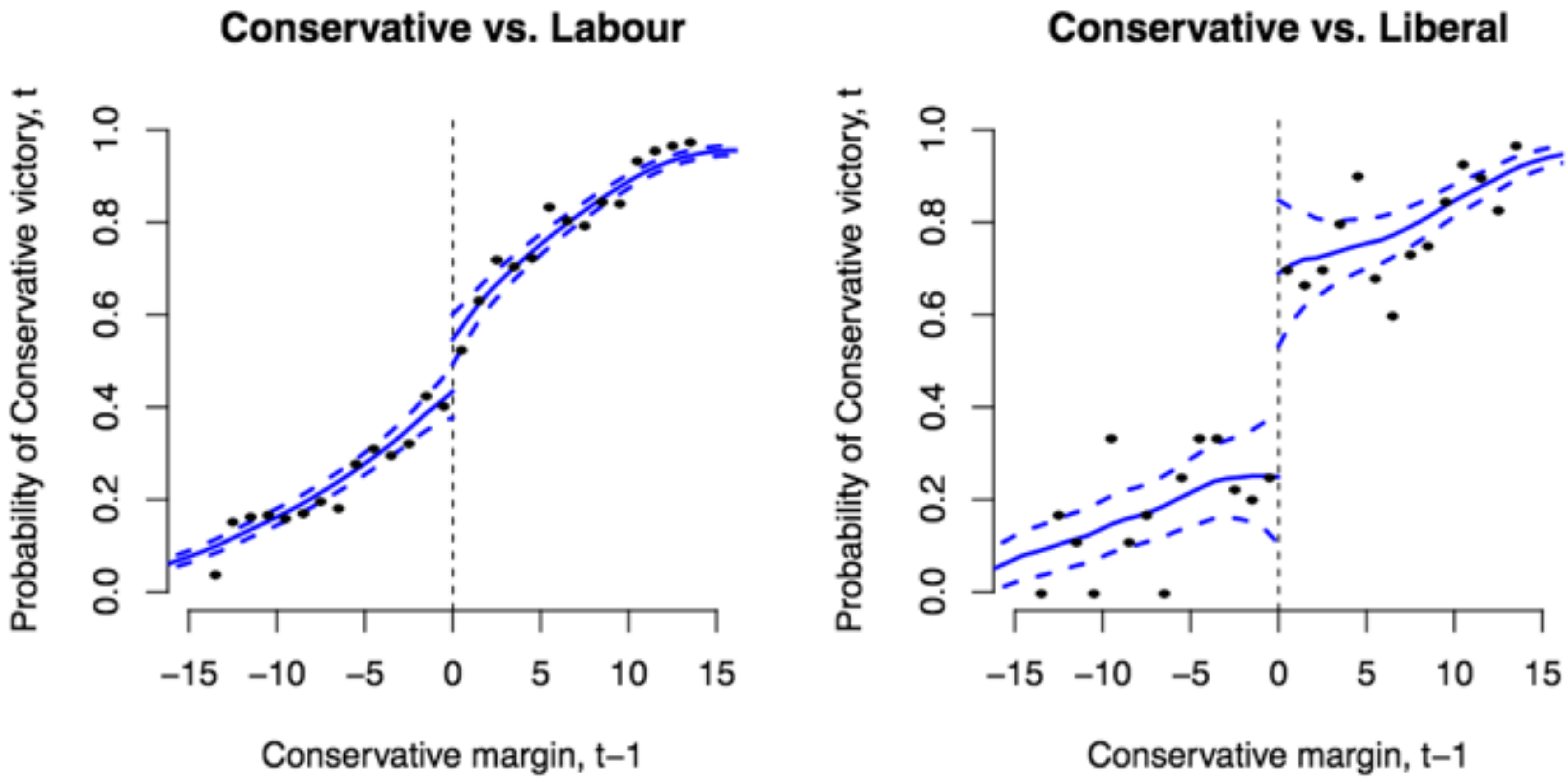
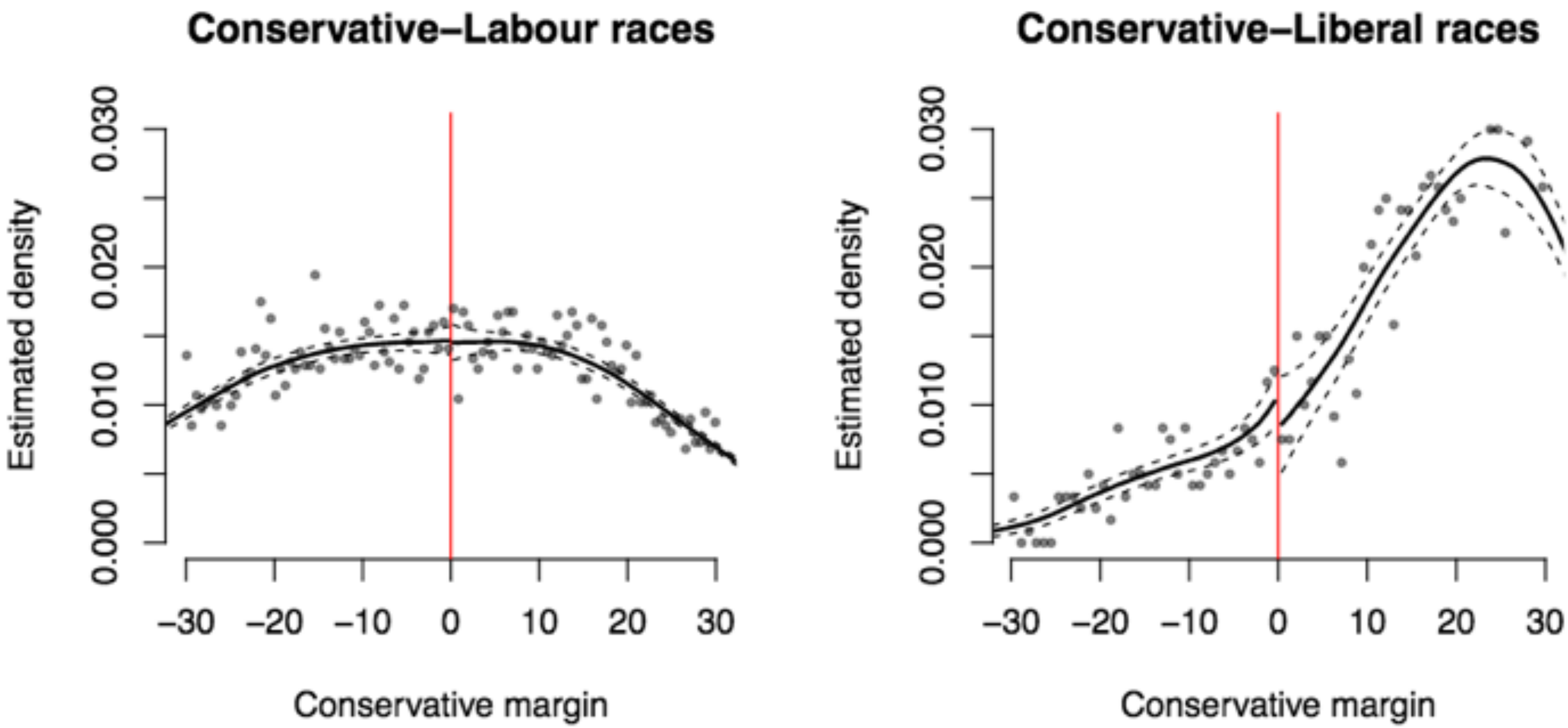


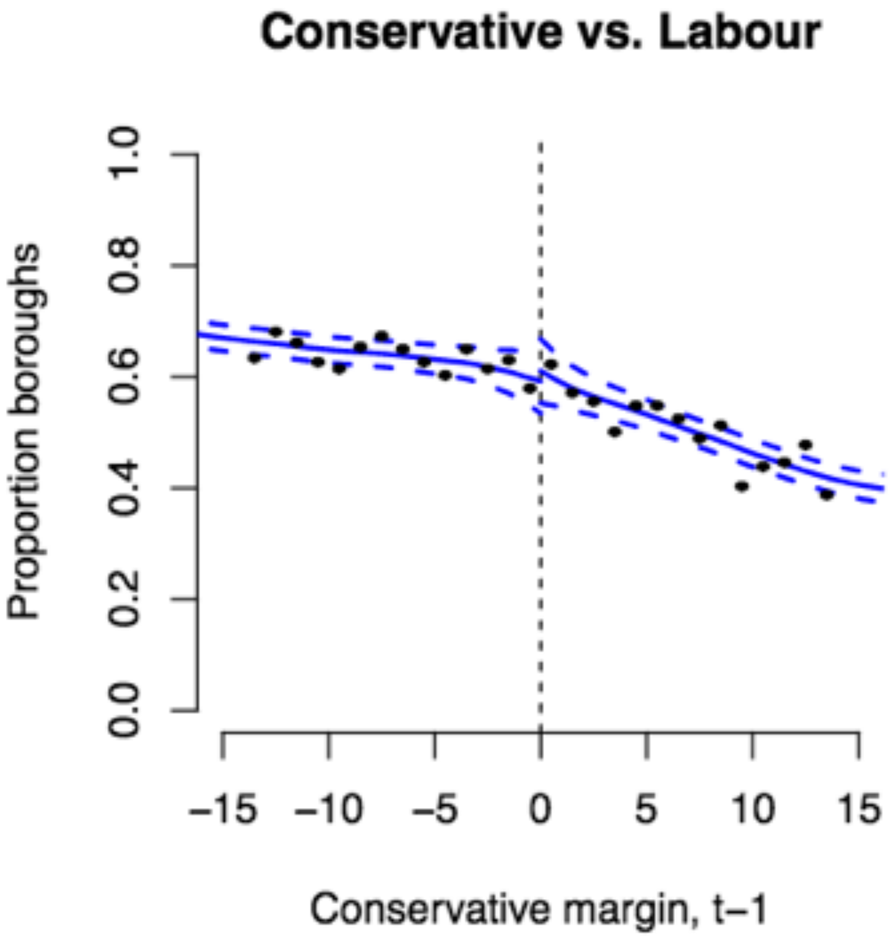
Example 1: tests of the continuity assumption (1)

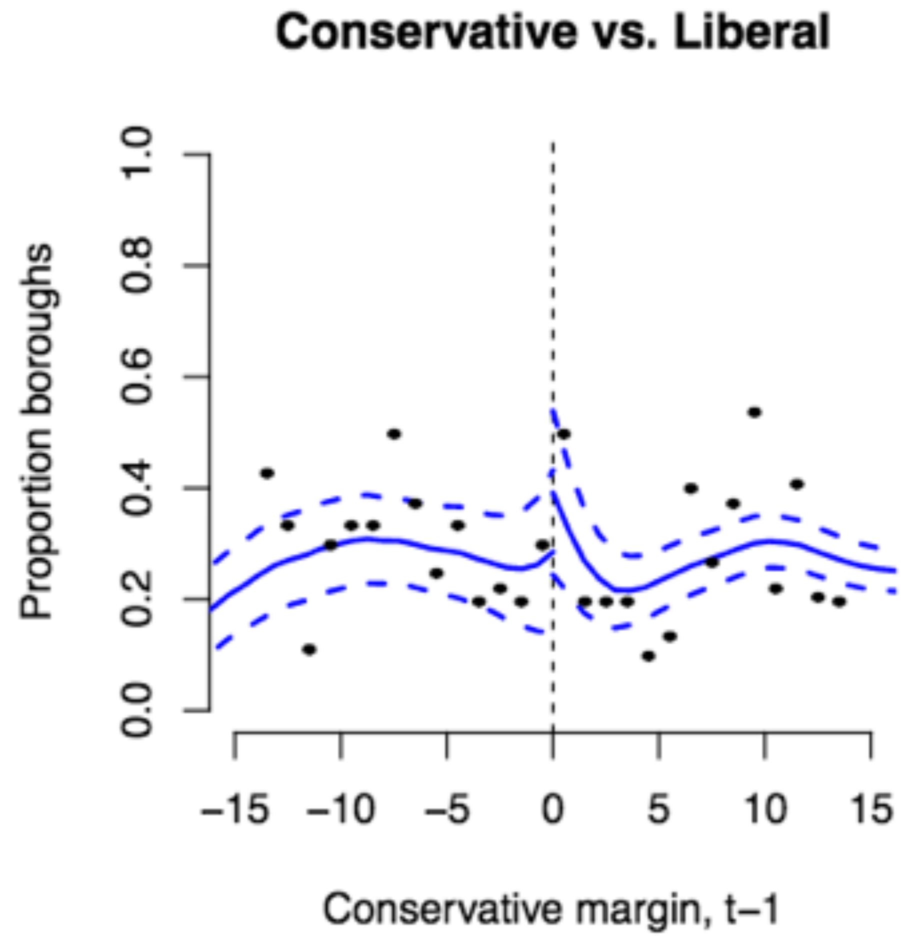
McCrary test for continuity in the density



Example 1: tests of the continuity assumption (2)

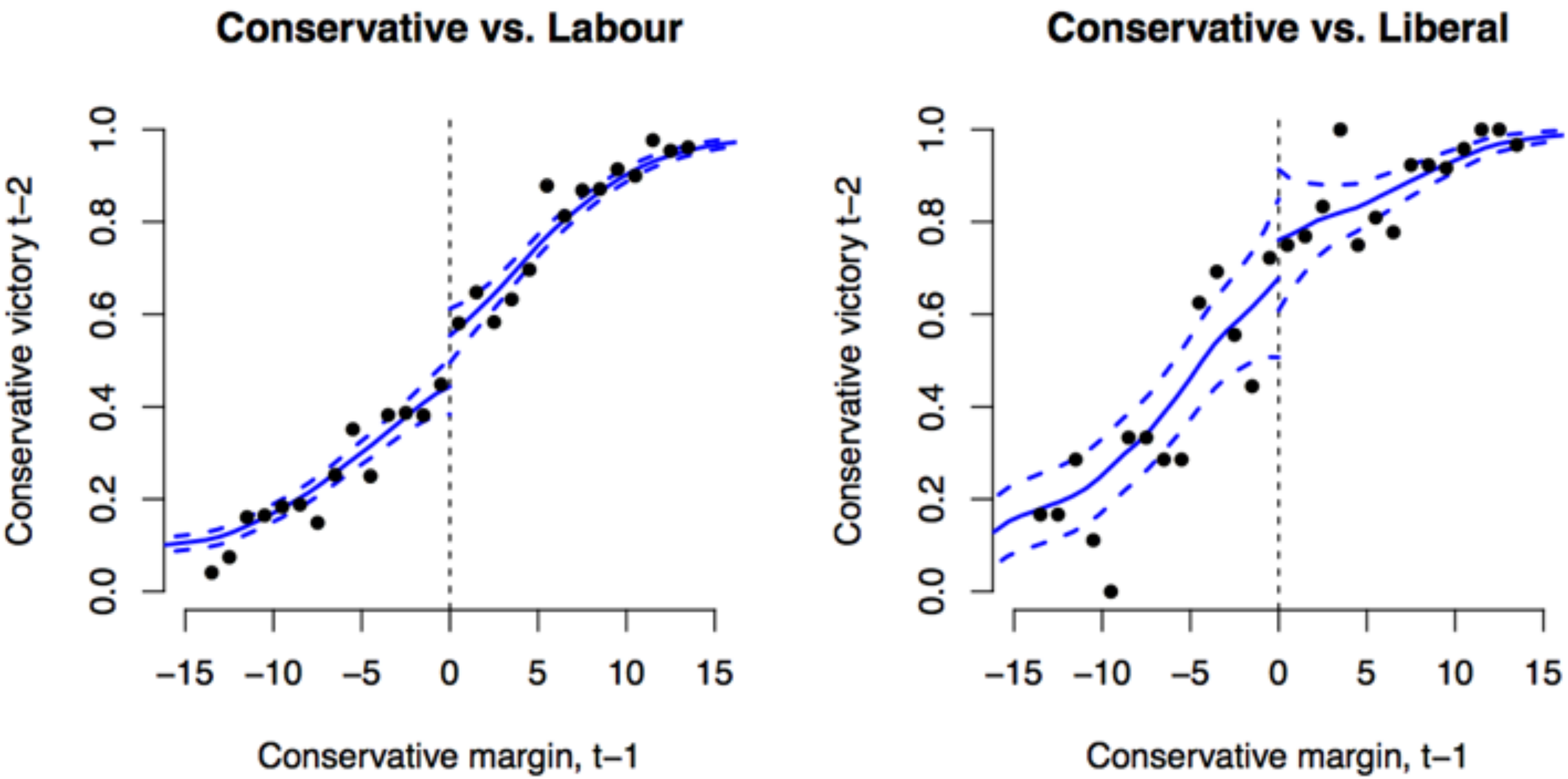
Tests for continuity in covariate: whether or not the election took place in a borough (vs county) constituency





Example 1: tests of the continuity assumption (3)

Tests for continuity in covariate: whether or not the Conservatives won the *previous* election



Example 2: Eggers (2015) on turnout and proportionality

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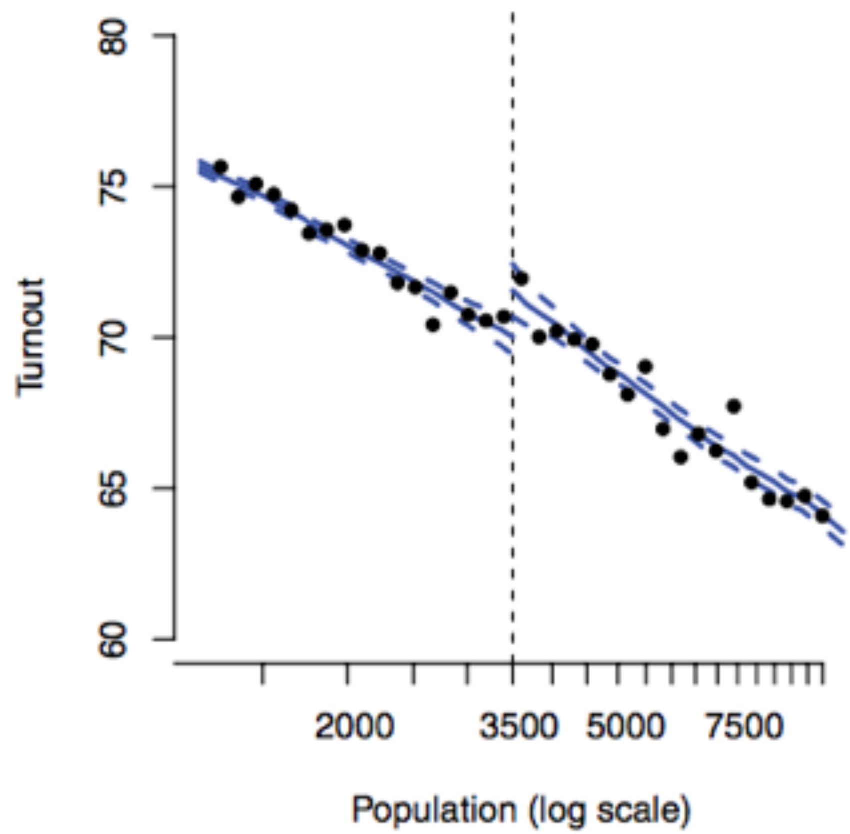
Turnout in 2001 municipal elections, by municipal population



Example 2: testing the continuity assumption

another. One standard way of checking the validity of the RDD, due to McCrary (2008), involves testing for a jump in the density of the forcing variable at the threshold; in this case, McCrary (2008)'s test fails to reject the null ($p = .127$). Another standard validity check is to carry out RDD analysis in which pre-treatment covariates serve as outcome variables. Table A1 in the appendix reports RDD effect estimates at varying population windows (25%, 50%, and 75%), showing that there is (as one would expect) no "effect" of crossing the 3,500 population threshold on the vast majority of placebo outcomes. These tests suggest that cities just above and below the population threshold are indeed comparable in not just observed but also unobservable features (e.g., local political culture). **(Page 144)**

Example 2: testing the continuity assumption (2)

Estimated effect of crossing 3,500 on turnout in municipal elections and higher-level elections

Outcome	Mean turnout	Effect (1)	Effect (2)	Effect (3)
Municipal, 2001	70.73	0.989	1.537**	1.525***
		(0.778)	(0.538)	(0.433)
Municipal, 2008	69.14	0.763	0.929†	1.476***
		(0.765)	(0.523)	(0.423)
Municipal, 2001 & 2008	69.96	0.878	1.242**	1.502***
		(0.71)	(0.481)	(0.385)
Presidential, 2002	74.95	−0.04	−0.189	−0.038
		(0.413)	(0.29)	(0.241)
Regional, 2004	63.38	−0.448	−0.7†	−0.241
		(0.583)	(0.414)	(0.341)
Presidential, 2007	86.33	−0.248	−0.439†	−0.253
		(0.326)	(0.224)	(0.185)
Window:	25%	25%	50%	75%

Example 2: testing the continuity assumption (3)

Table A1. RDD Analysis: The Effect of Crossing the 3,500 Population Threshold on Placebo (Pre-Treatment) Outcomes.

		Effect estimates		
Outcome	*Mean*	(1)	(2)	(3)
Pct. retired, 1999	19.07	0.711	0.313	0.24
		(0.667)	(0.455)	(0.361)
Pct. working in agriculture, 1999	5.34	−0.023	−0.068	0.775*
		(0.638)	(0.461)	(0.38)
Pct. with "bac" degree, 1999	36.45	−0.713	−0.758	−0.187
		(0.985)	(0.718)	(0.585)
Pct. unemployed, 2001	12.33	−0.764	−0.456	0.064
		(0.762)	(0.542)	(0.441)
Log pop., 1990	8.03	0.025†	0.013	0.011
		(0.013)	(0.009)	(0.007)
Area (sq. km.)	21.37	−3.087	−1.883	−1.803
		(2.021)	(1.406)	(1.123)
Local tax revenue, 2000 (in thous. euros)	1,142.57	172.027	125.215	109.848
		(106.377)	(75.952)	(66.66)
VAT compensation fund (FCTVA), 2000 (in thous. euros)	101.36	5.422	4.661	6.406
		(8.829)	(6.544)	(5.628)
Turnout, 1995 pres. elections	81.87	−0.157	−0.057	−0.109
		(0.341)	(0.236)	(0.192)
Pct. for Chirac, 1995 pres. elections	51.87	0.633	0.772	0.585
		(0.927)	(0.674)	(0.541)
Region: Center	0.08	−0.033	−0.006	−0.005
		(0.028)	(0.019)	(0.016)
Region: West	0.22	−0.005	−0.076*	−0.084***
		(0.044)	(0.031)	(0.025)
Region: South	0.22	0.018	0.042	0.052†
		(0.045)	(0.032)	(0.026)
Region: East	0.13	0.046	0.044	0.013
		(0.037)	(0.027)	(0.022)
Region: North	0.16	−0.019	0.004	0.018
		(0.039)	(0.028)	(0.023)
Region: SW	0.13	0.013	0.003	0.015
		(0.037)	(0.026)	(0.021)
Region: Paris	0.06	−0.021	−0.01	−0.01
		(0.026)	(0.019)	(0.015)
Window	25%	25%	50%	75%

Does RDD work for political science applications? The case of close elections

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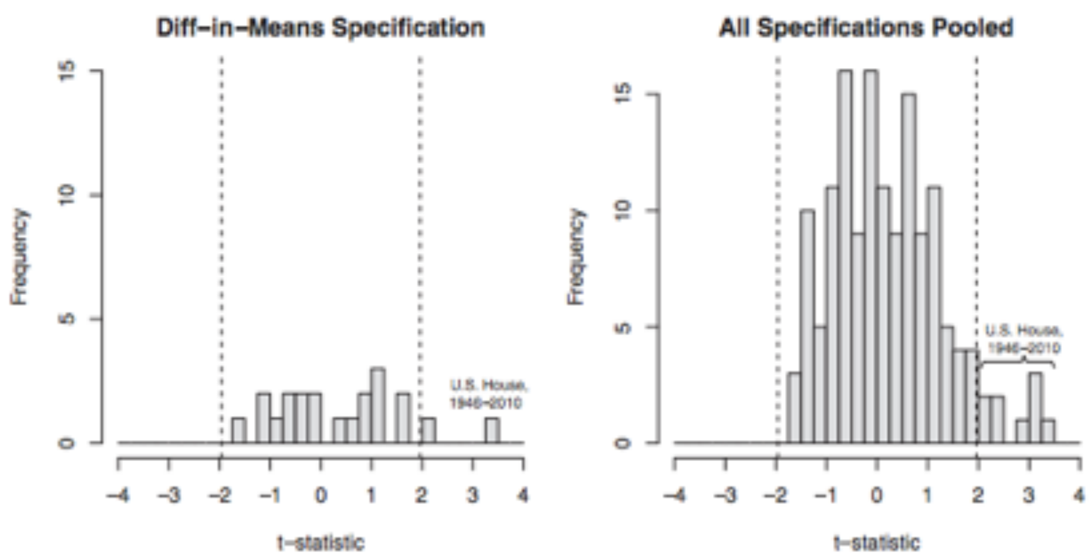
FIGURE 2 T-values for "Effect" of Party Winning at Time t on Party Winning at Time t − 1



Does RDD work for political science applications? The case of population thresholds (1)

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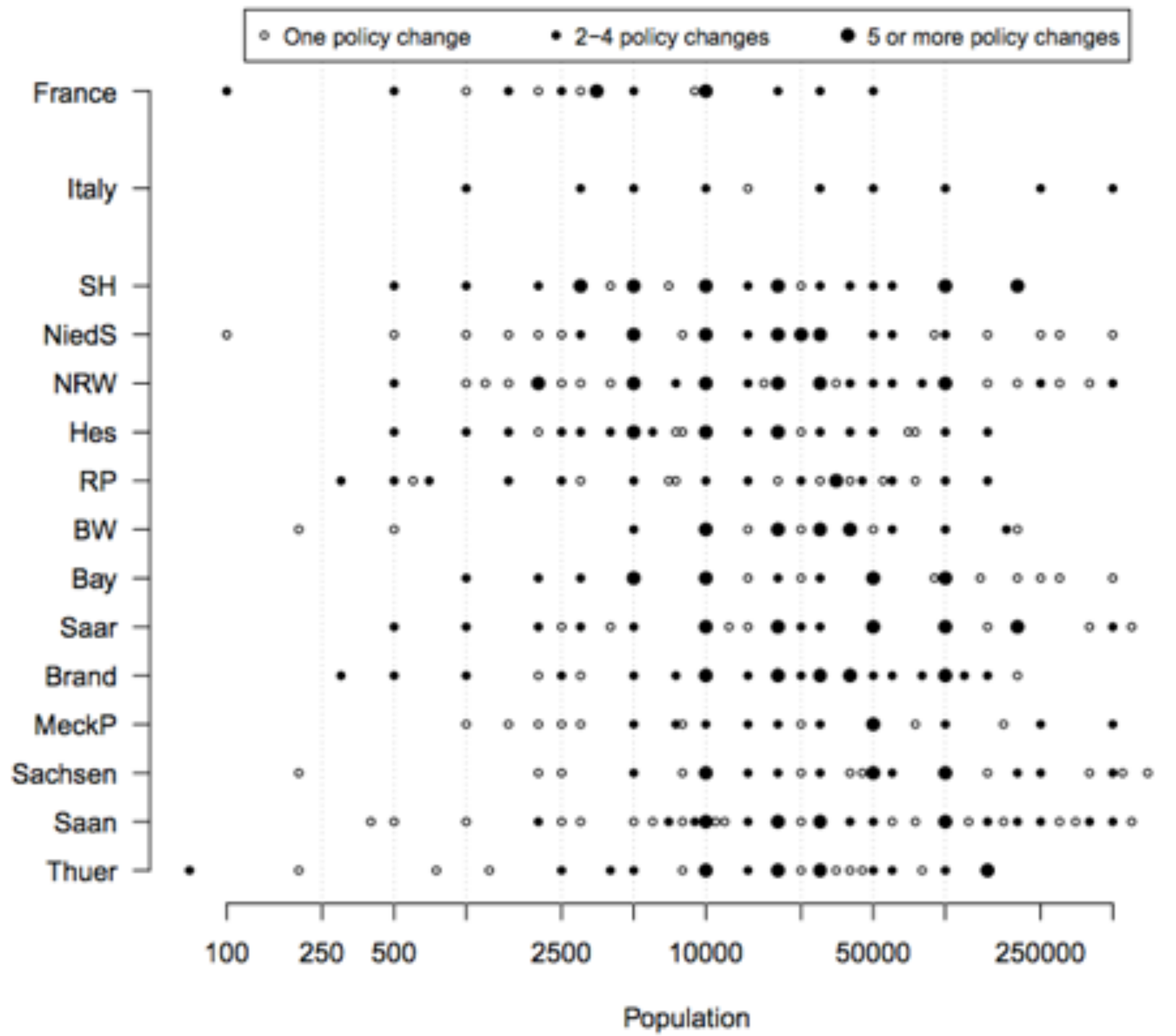
First problem: same threshold often used to determine more than one treatment.

See Eggers, Freier, Grembi, Nannichini (forthcoming) and Eggers (2015) for ideas about handling this.



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Second problem: **sorting**. Consider histograms of population in French villages near 1,000 in pop., where mayor's salary increases:

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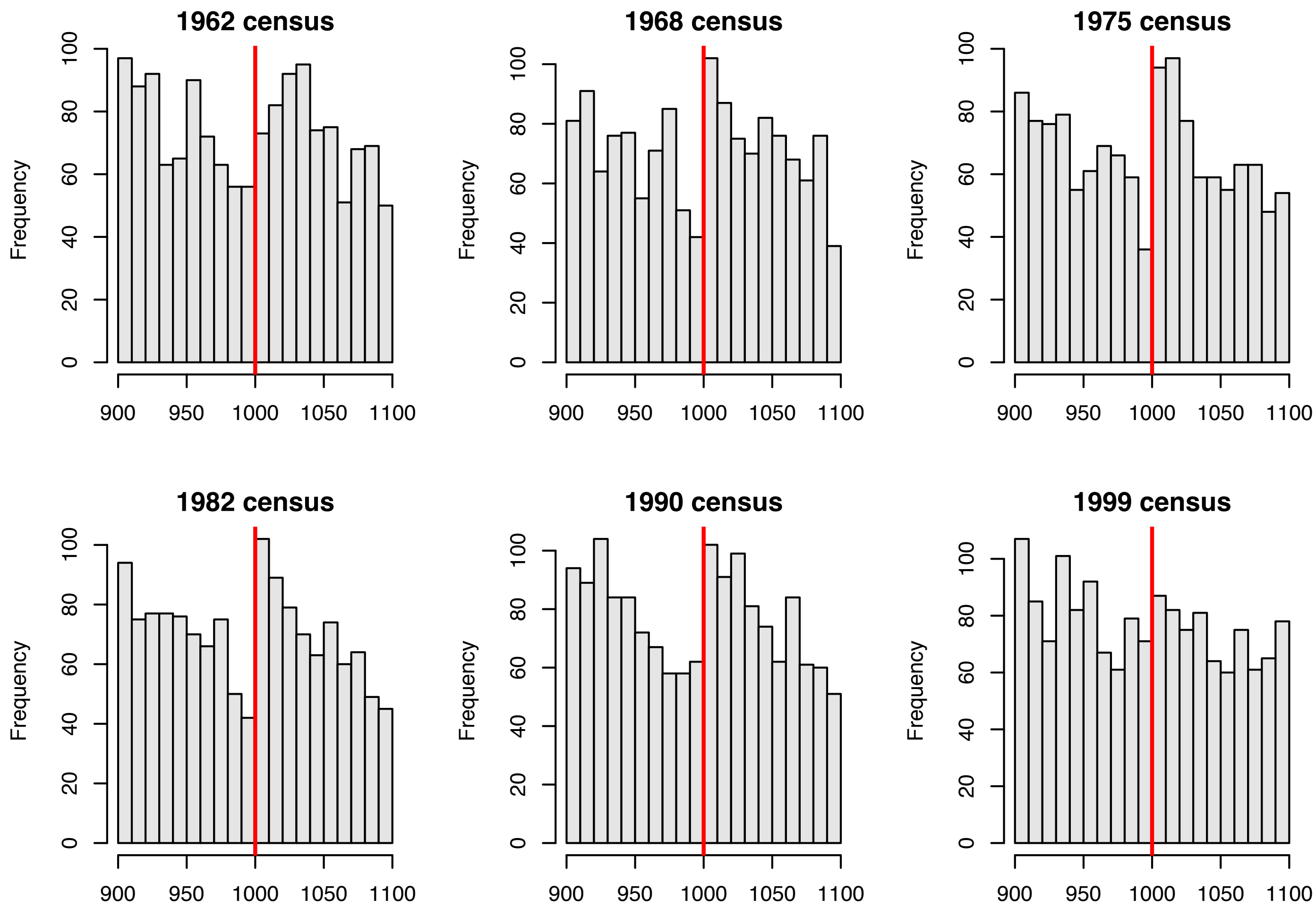
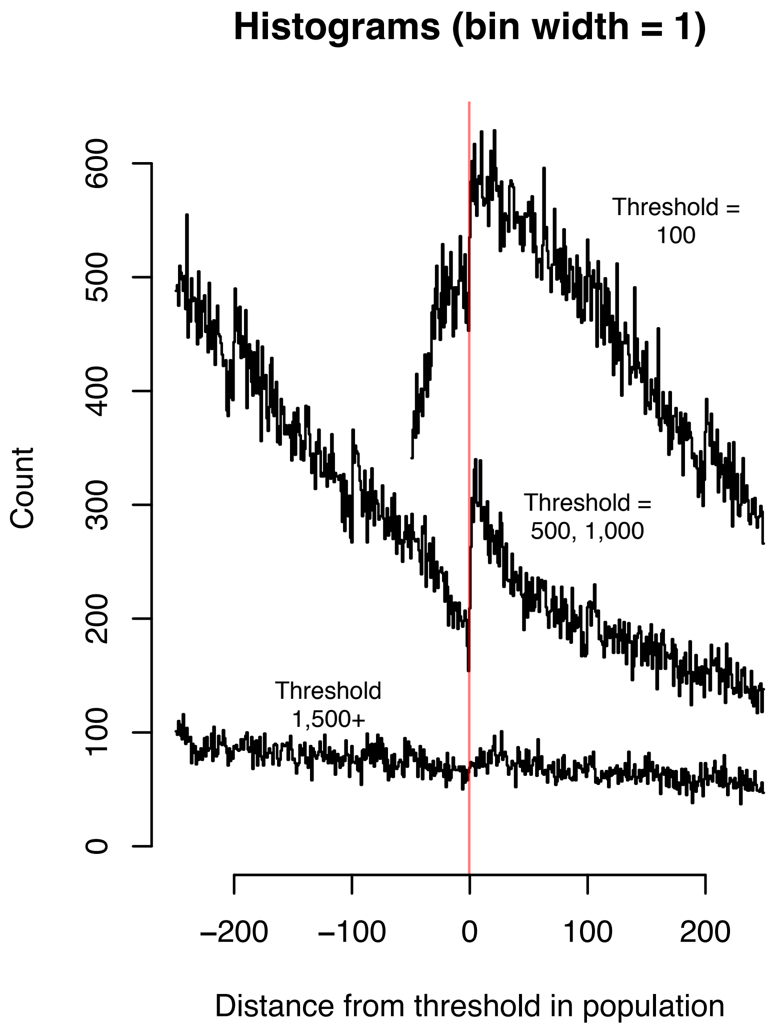
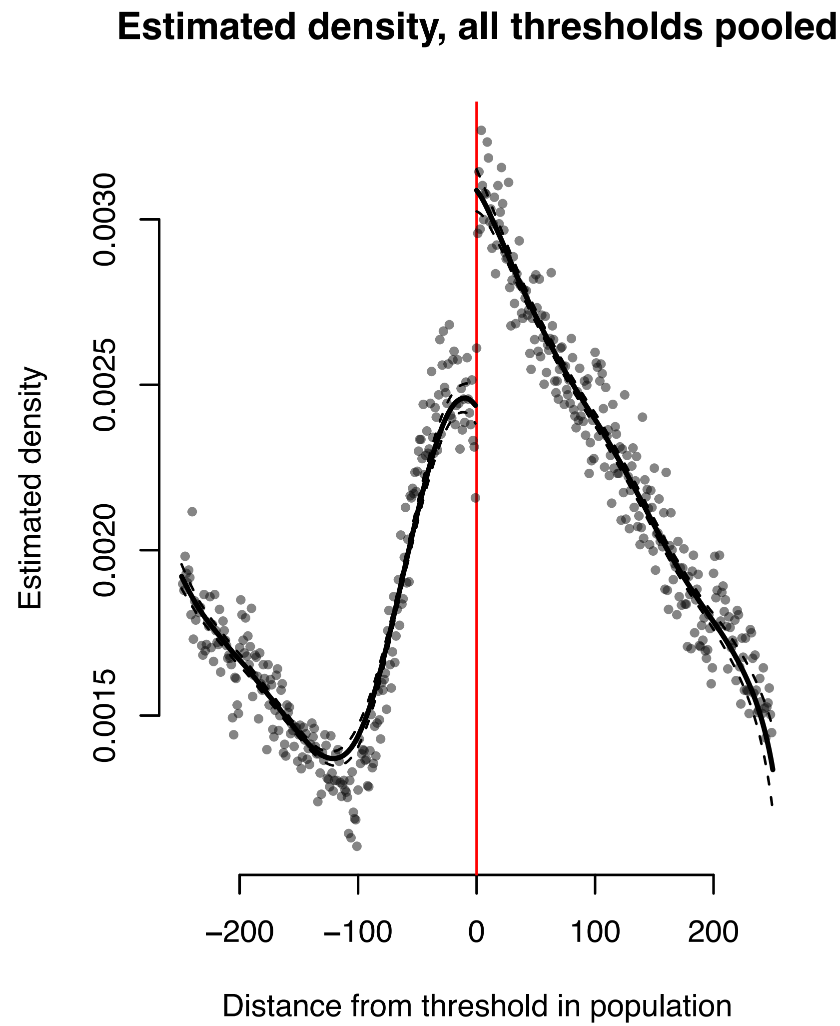


Does RDD work for political science applications? The case of population thresholds (3)

Pooling all thresholds, censuses from France:





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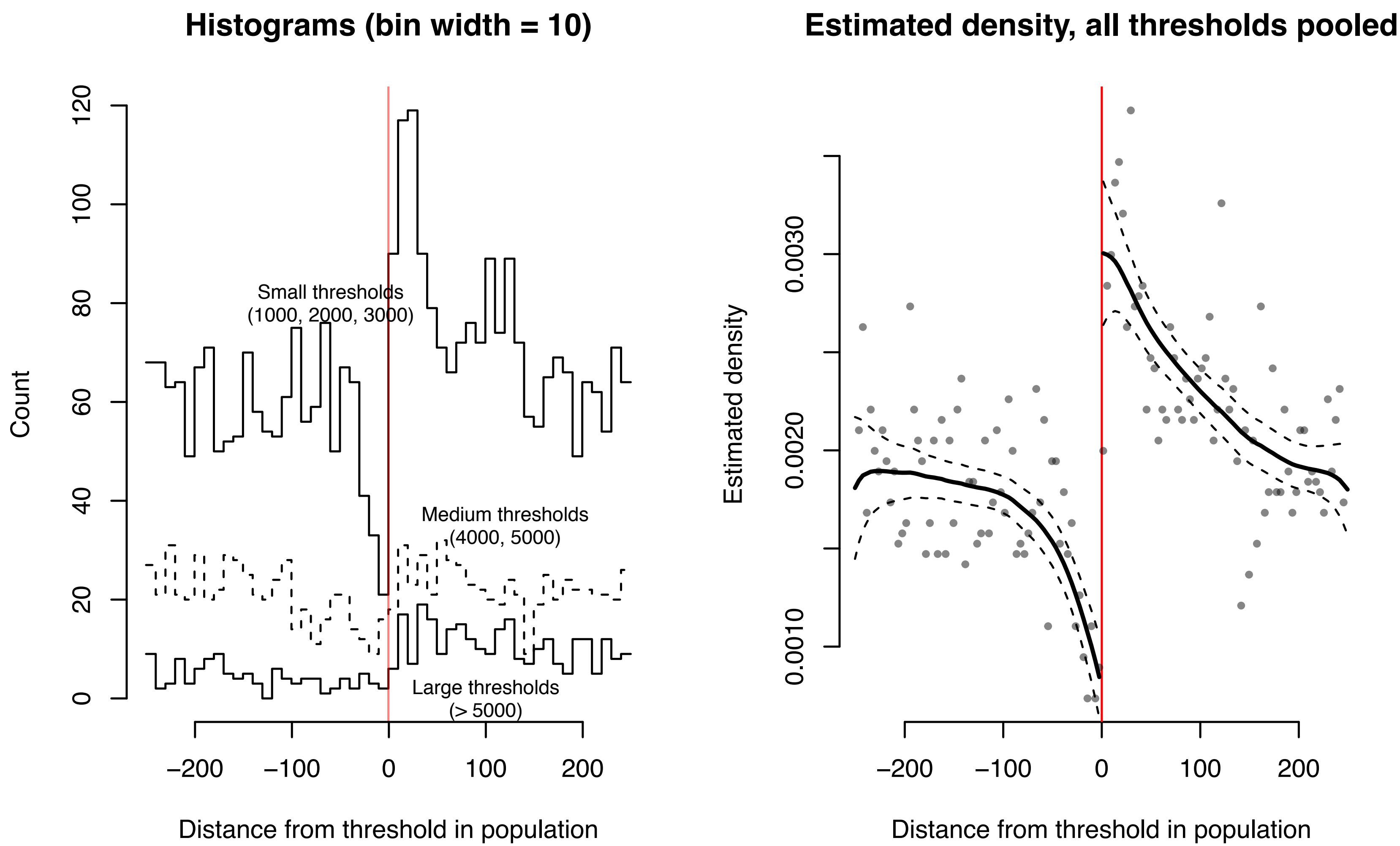
Even worse in Italy:



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(2) If there is sorting, is the RDD ruined?

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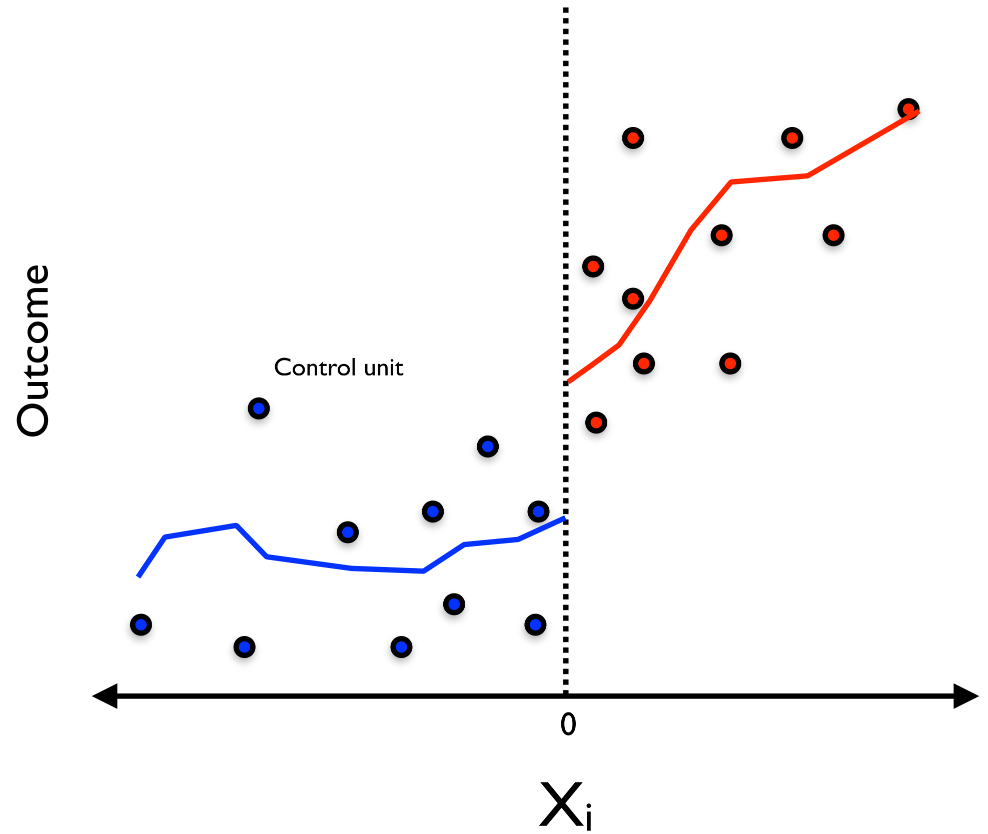
So, how do we do it?

Over past 10 years, much variety. Something simple gets complicated!

Local linear regression approach

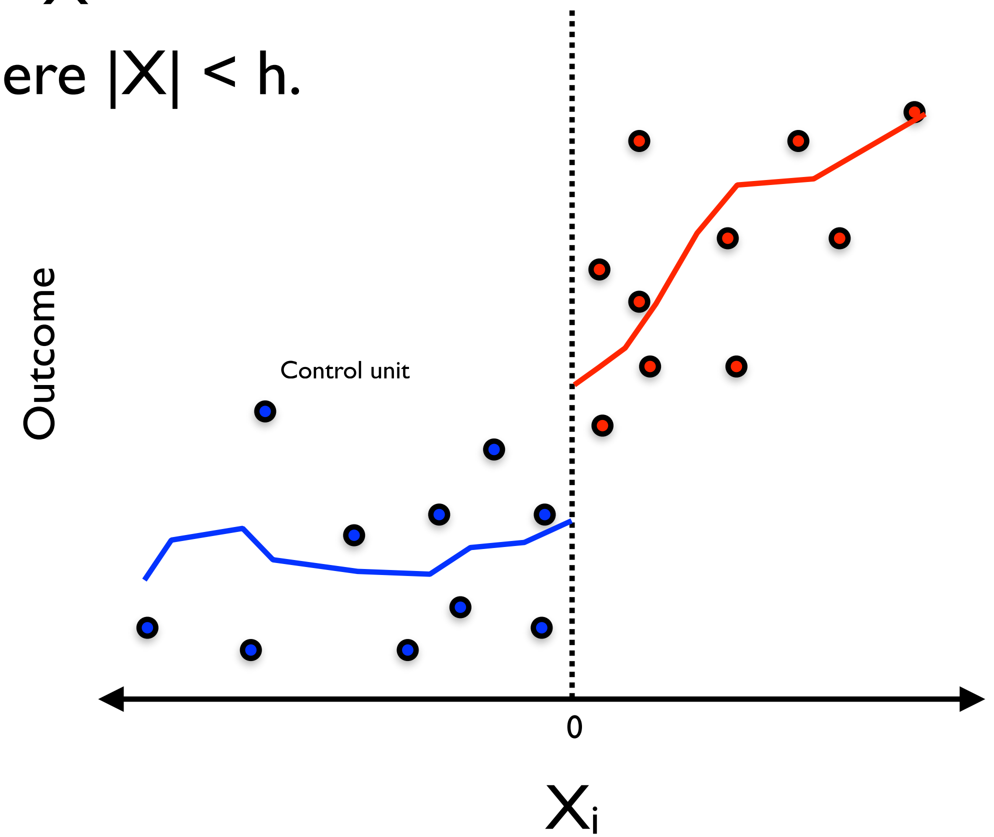


Local linear regression approach

Consider running this regression:

$Y = \beta_0 + \beta_1 D + \beta_2 X + \beta_3\, D \times X$

restricting to observations where $|X| < h$.



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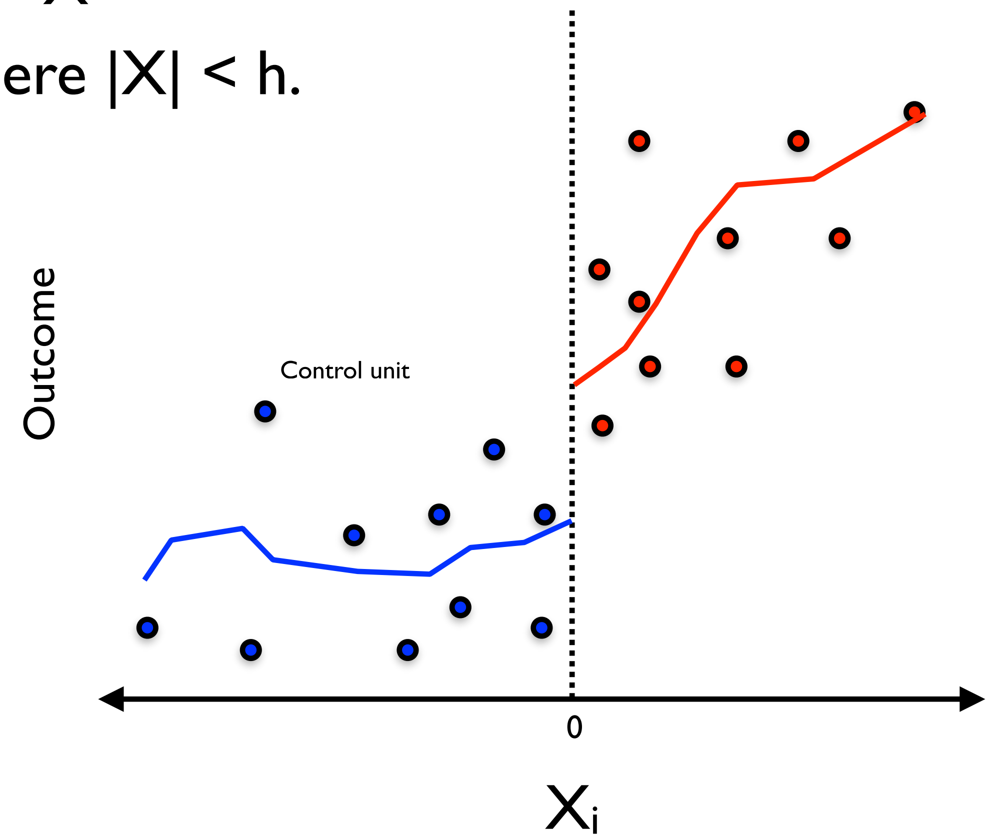

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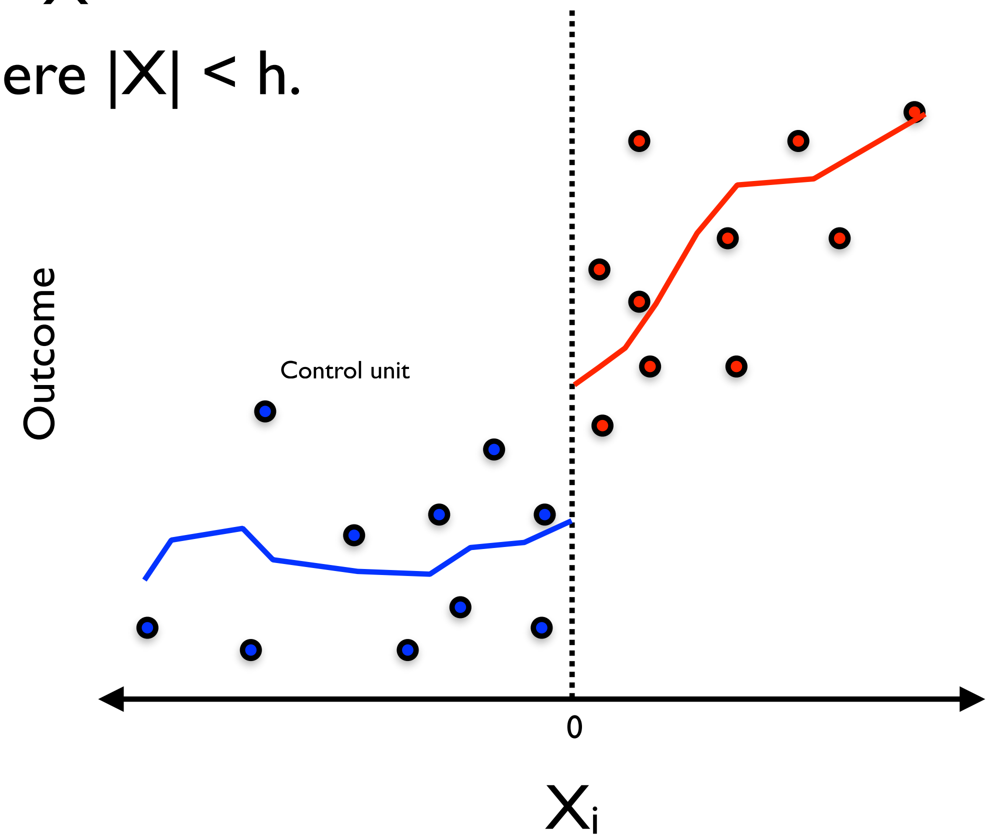

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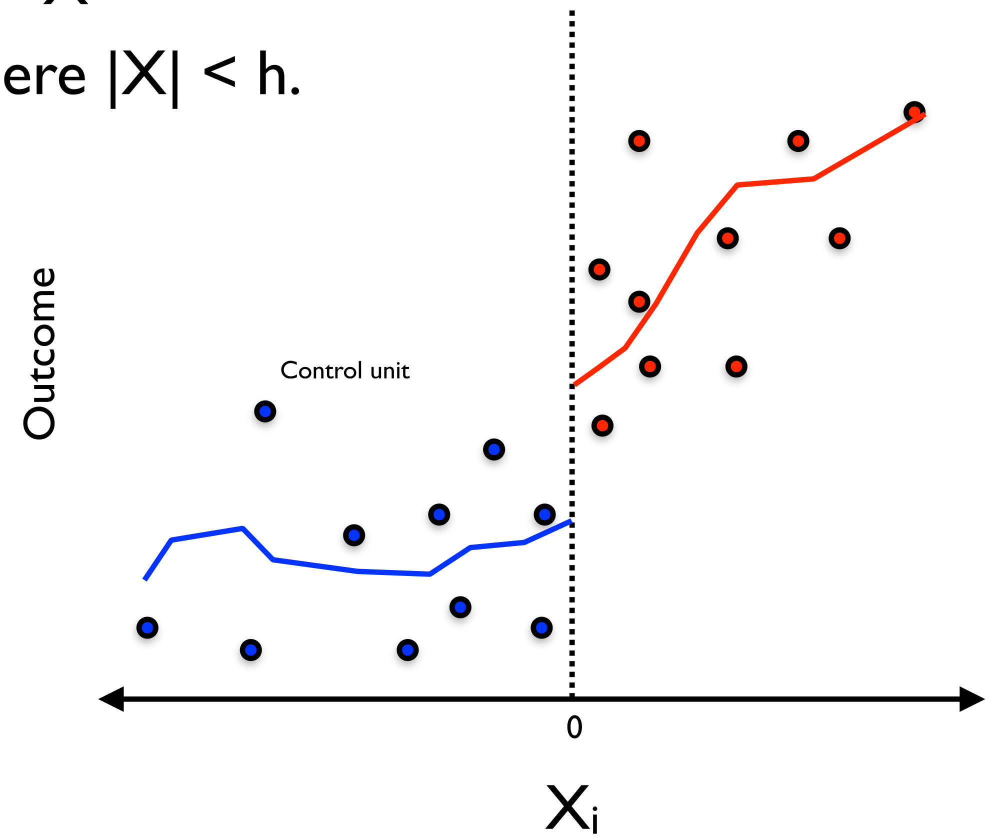

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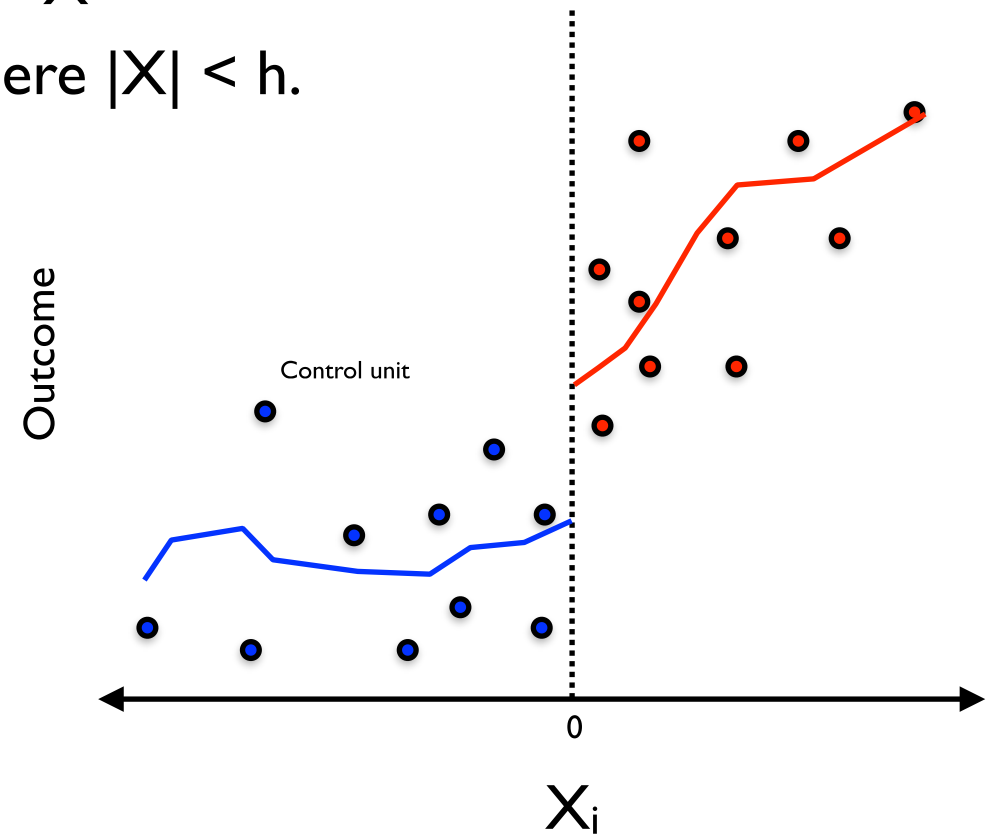

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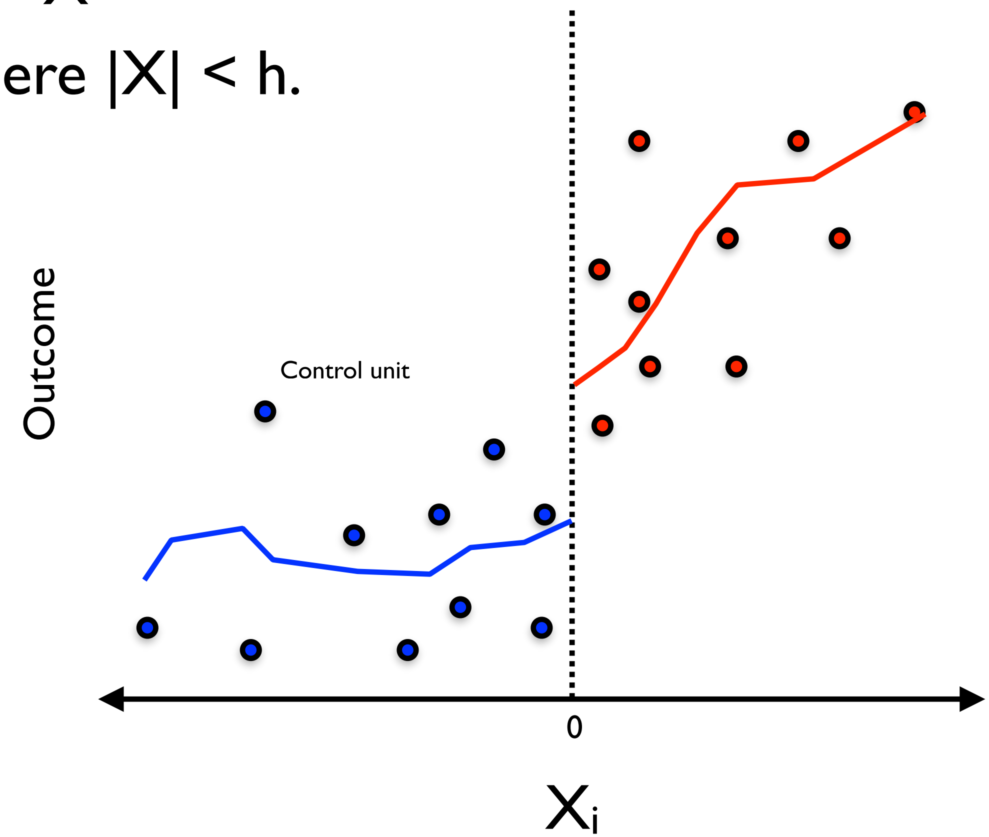
There is a **bias-variance tradeoff**.



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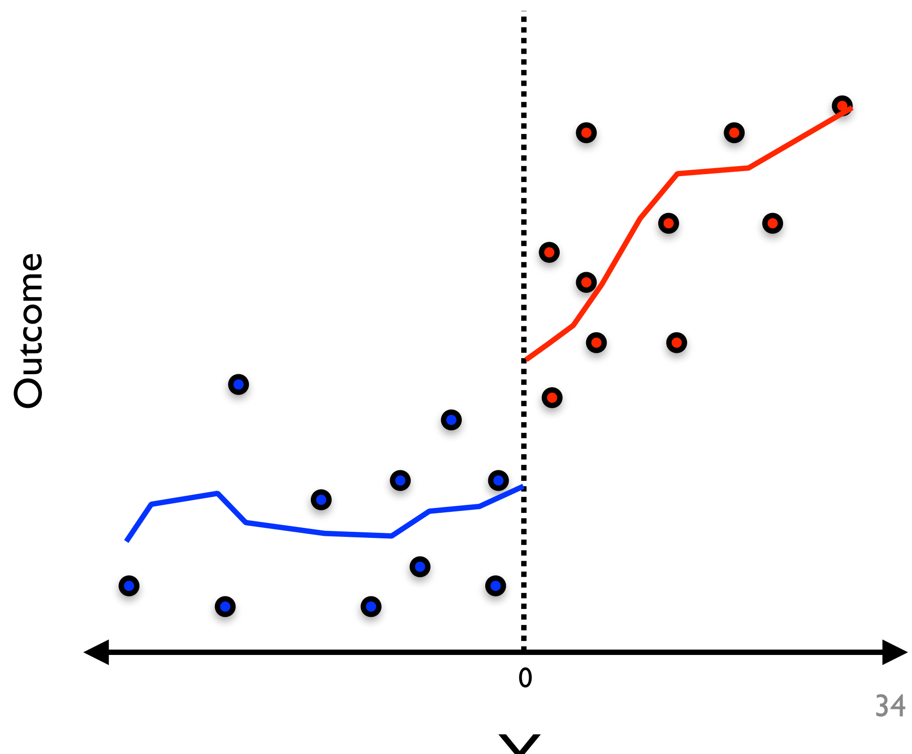

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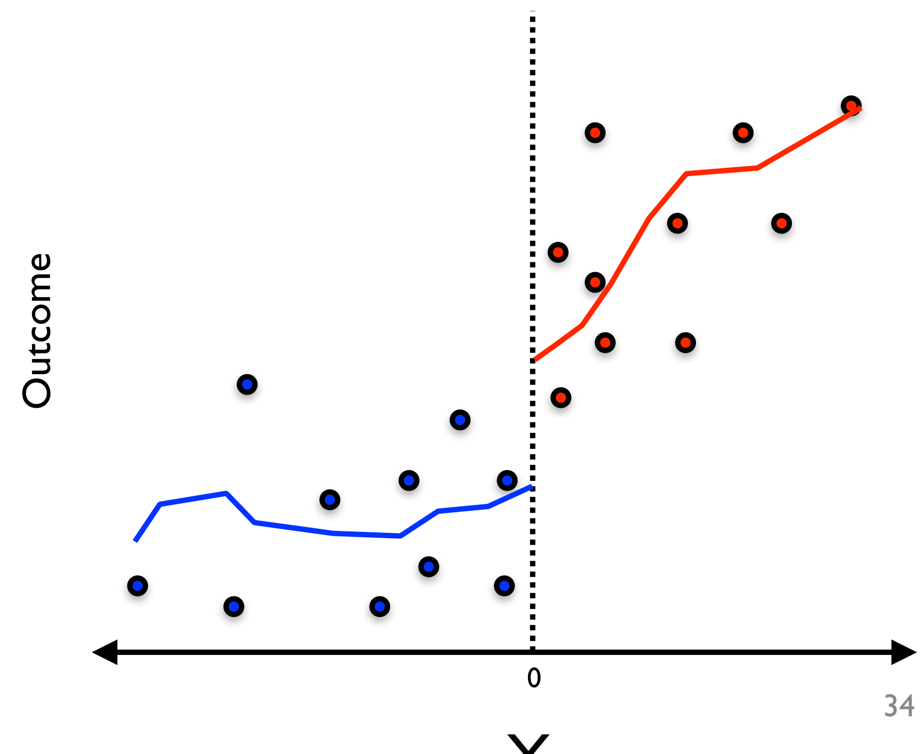

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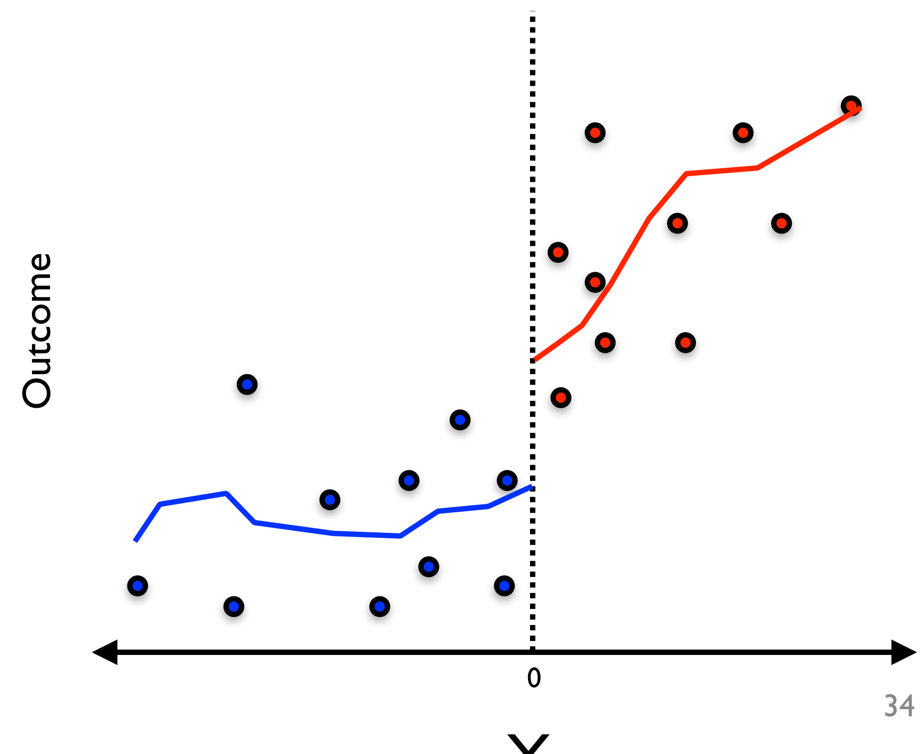

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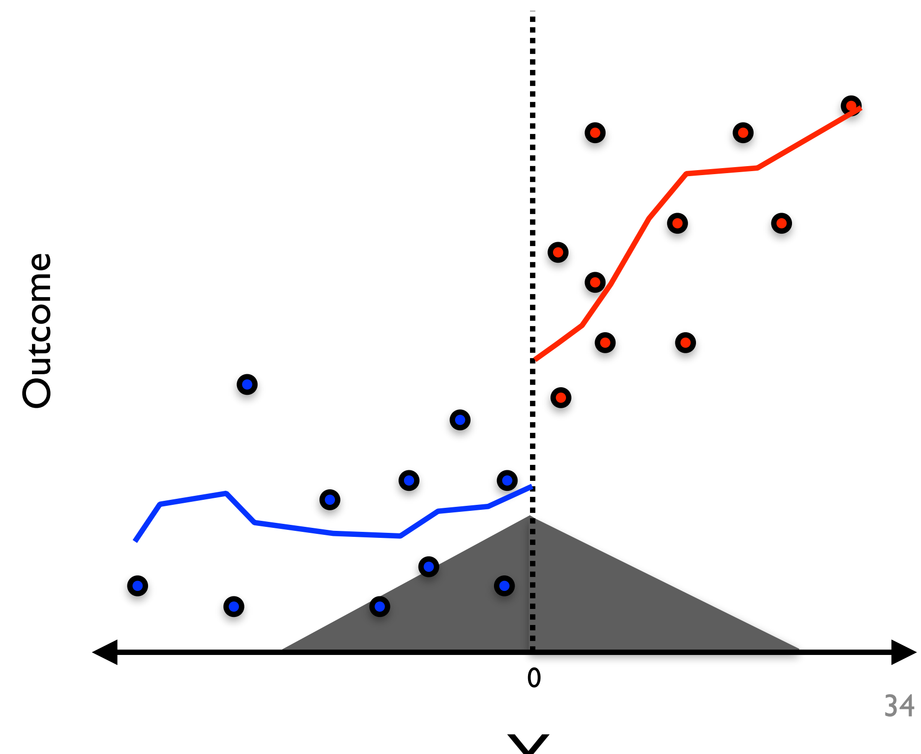

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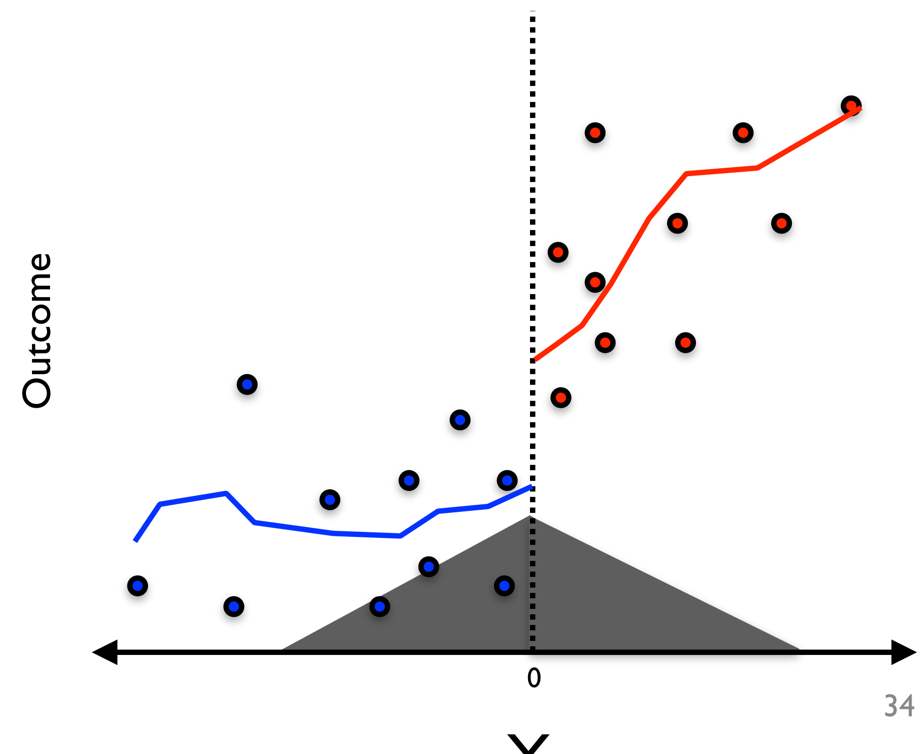

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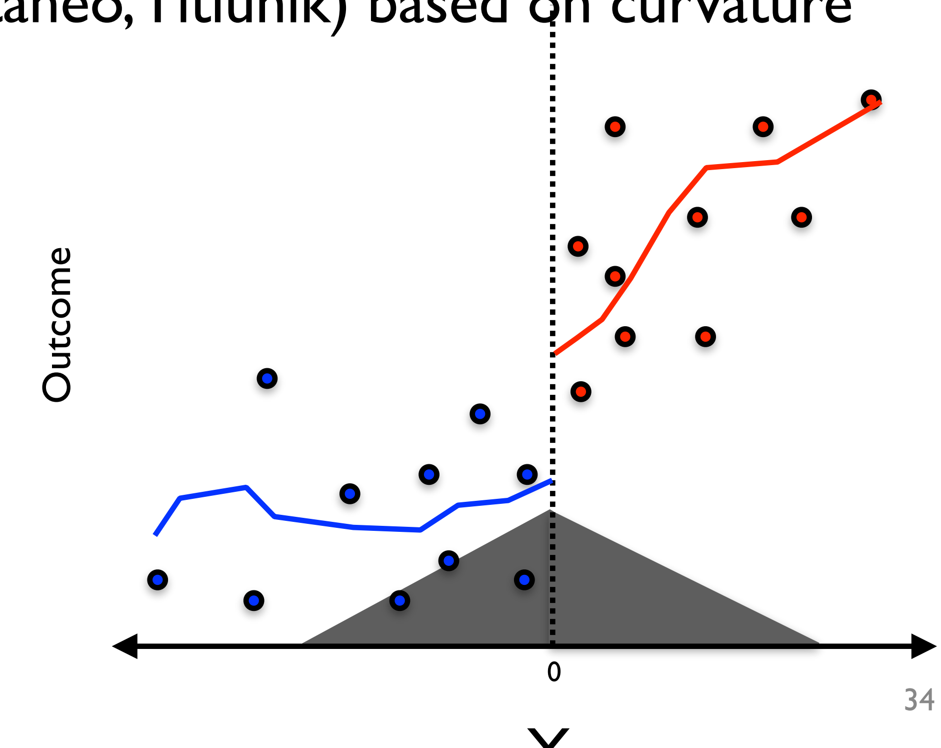

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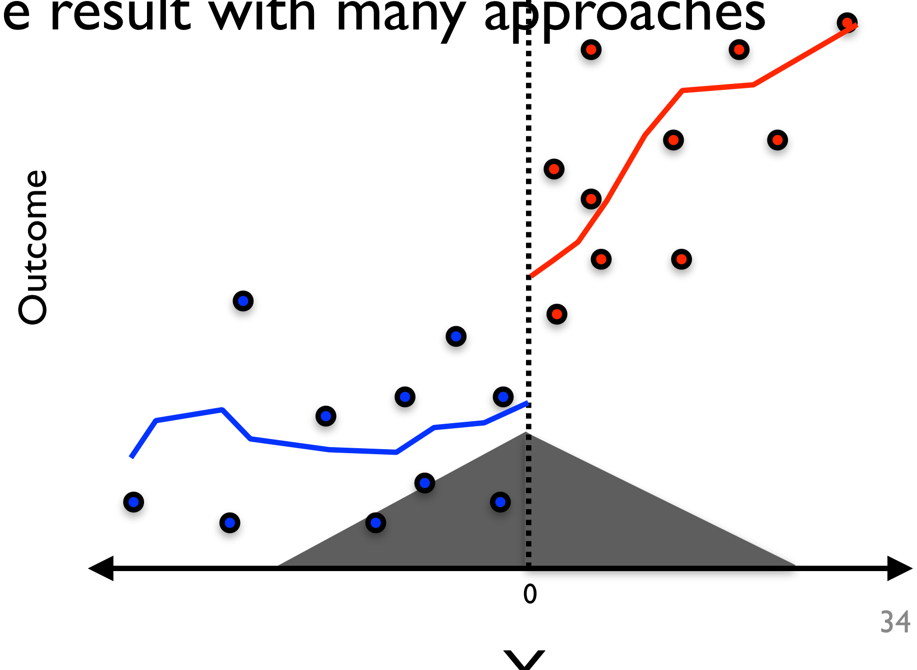

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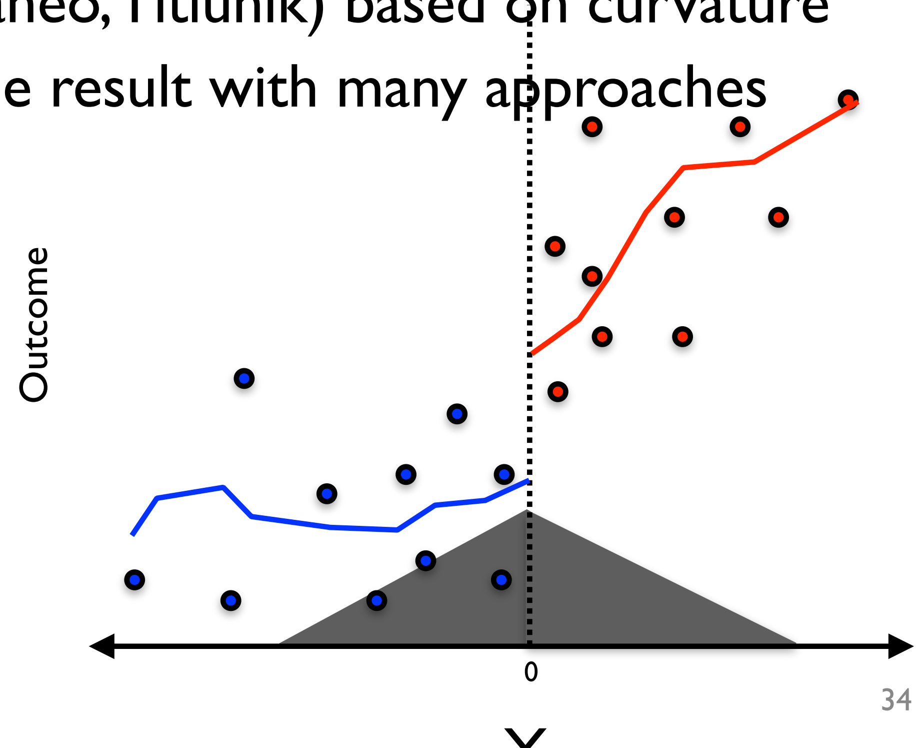
State of the art: `rdrobust` package (Stata, R), other work by Calonico, Cattaneo, Titiunik

Rocío Titiunik



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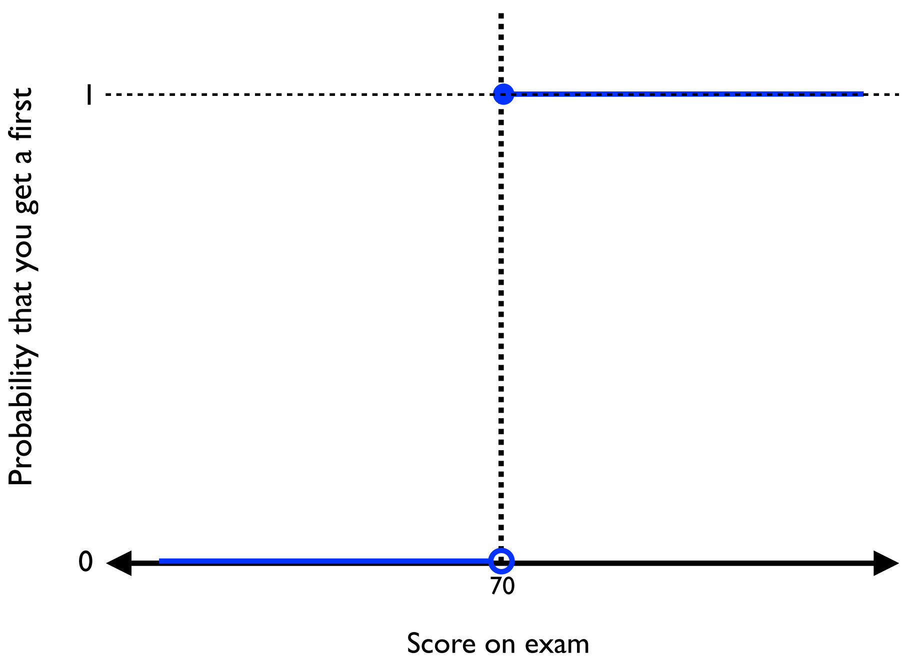

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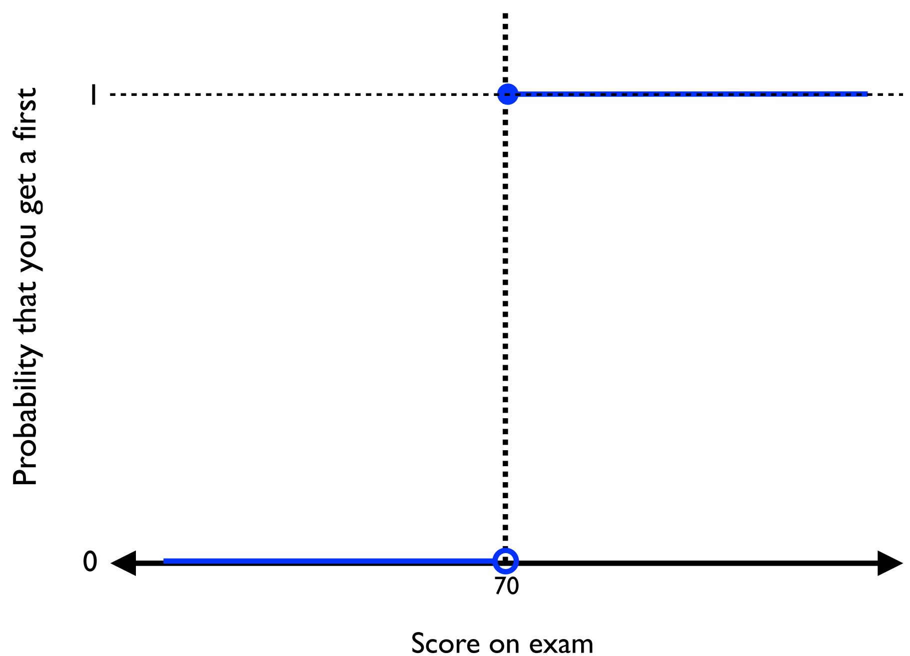
Sharp RDD.



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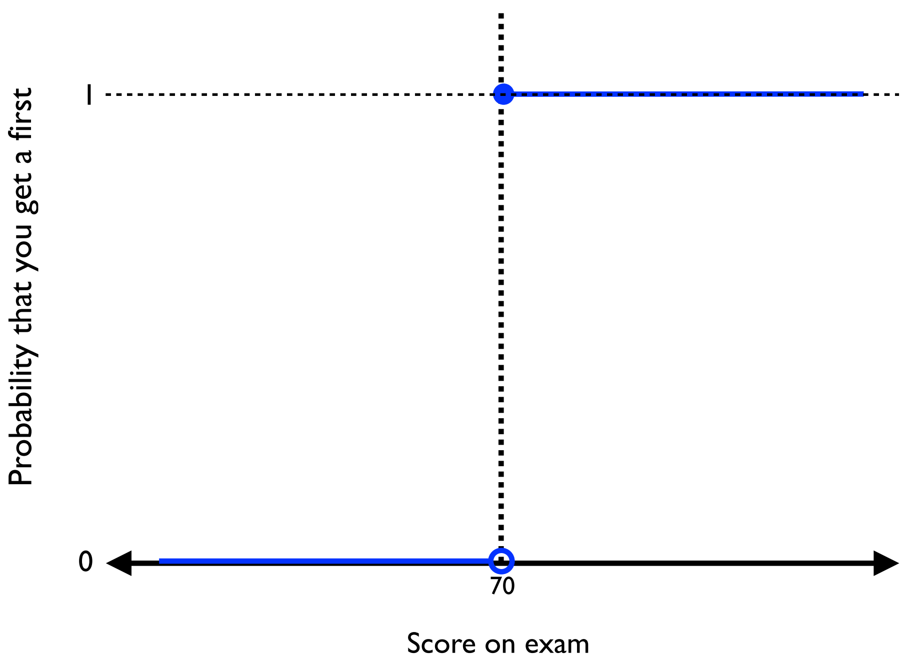

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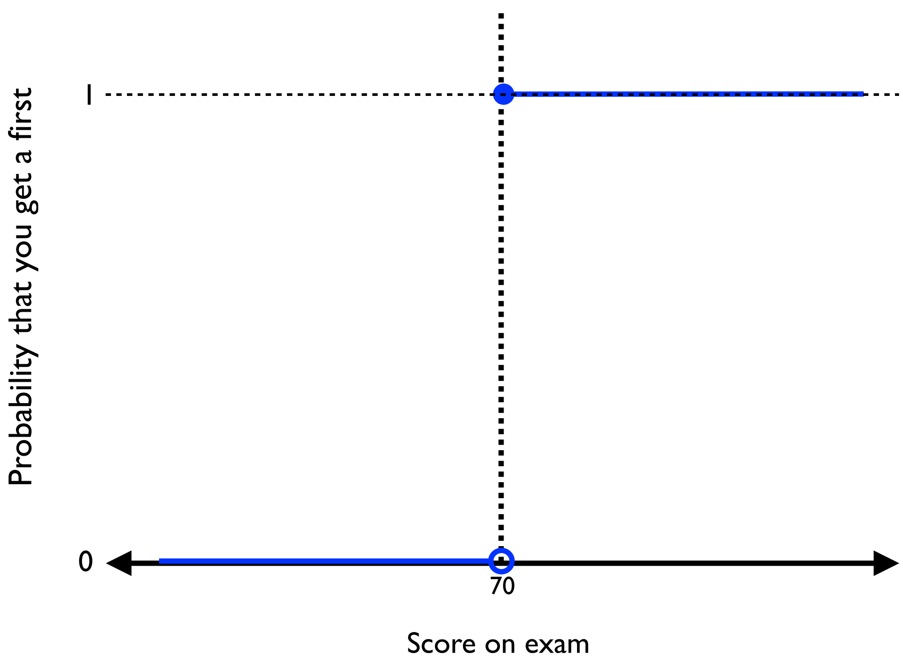

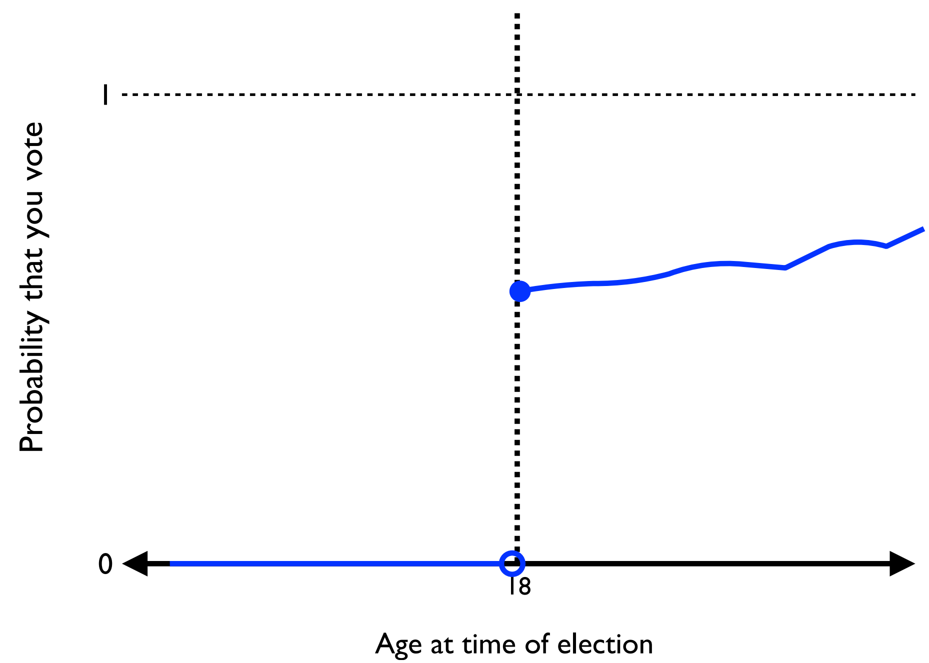

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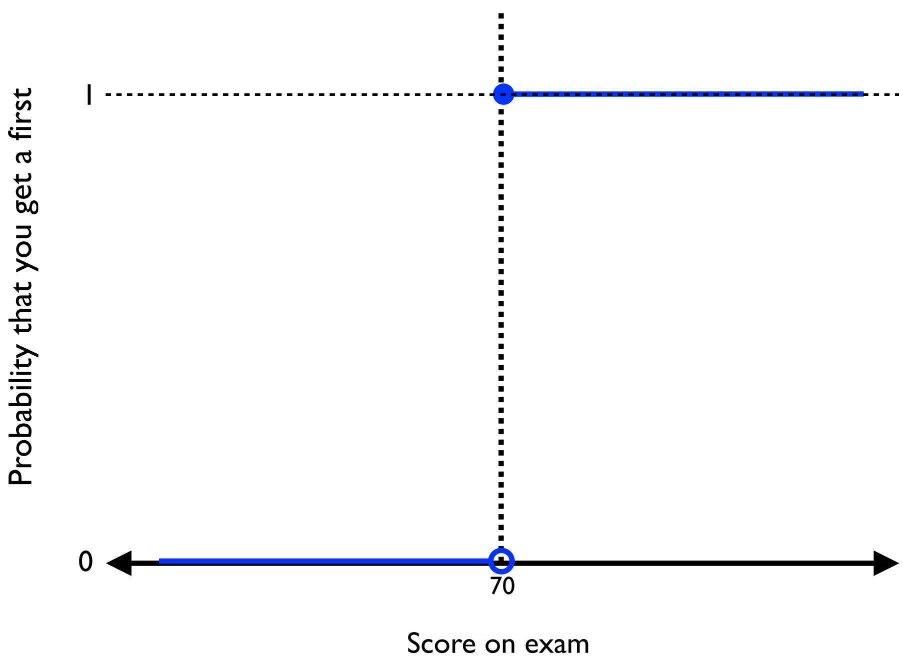

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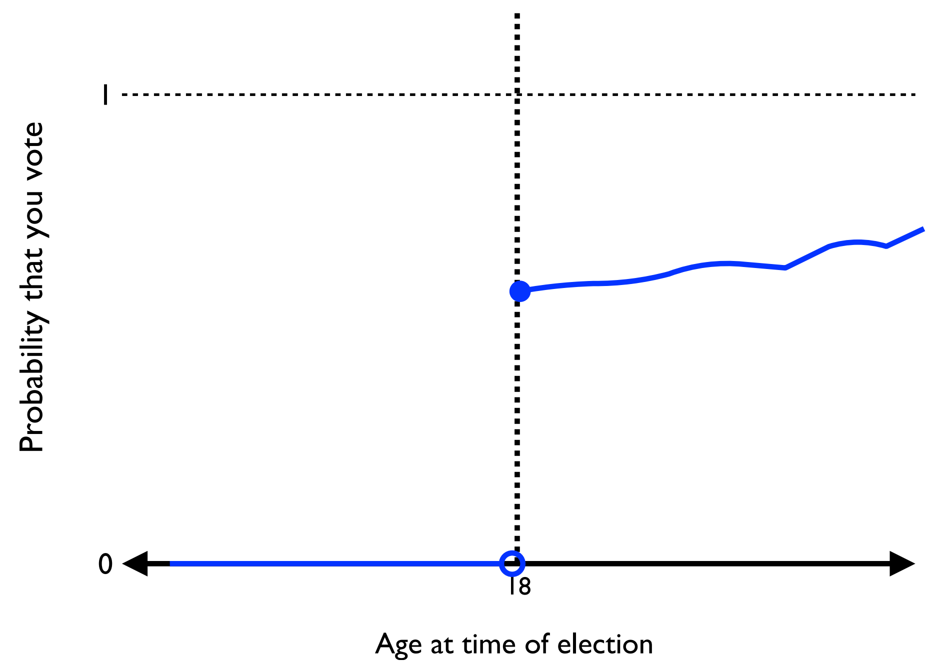

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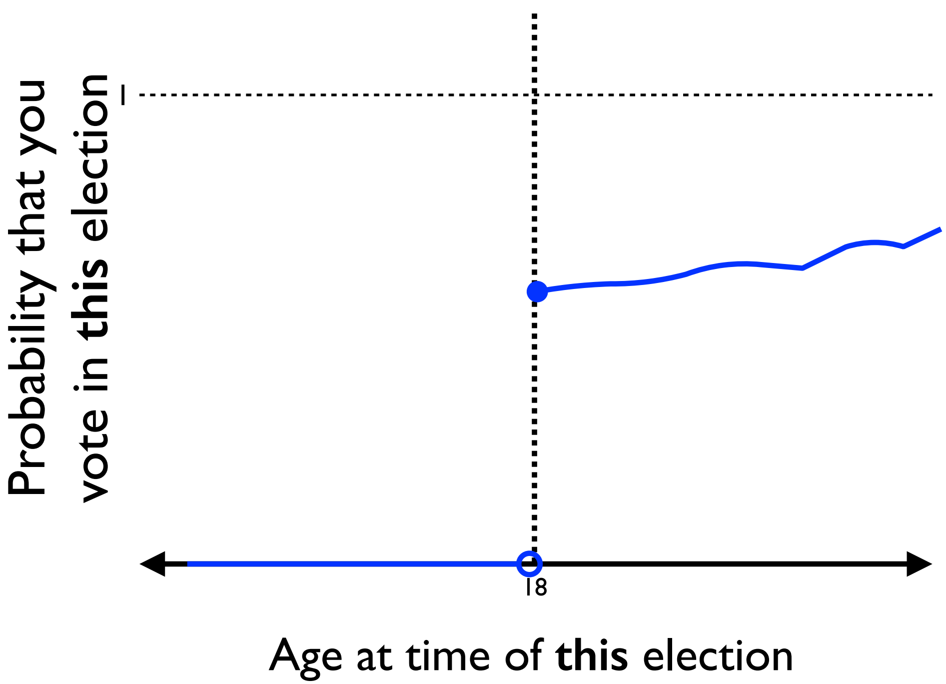

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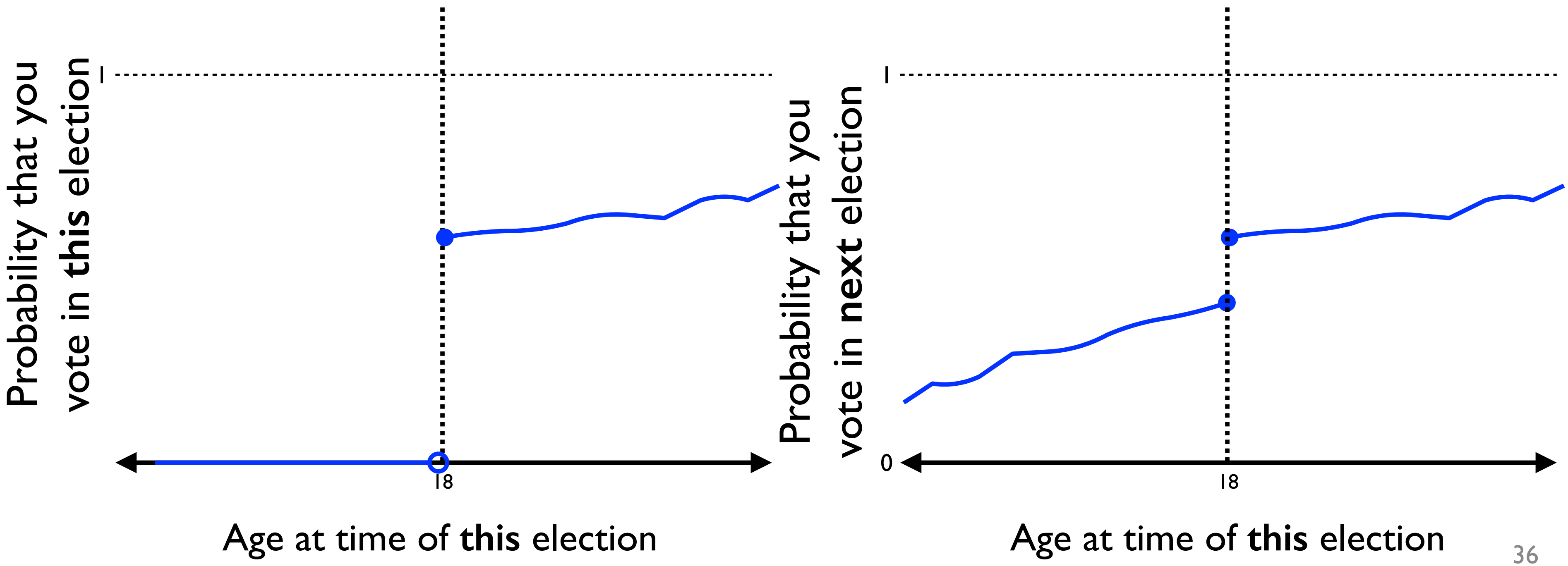

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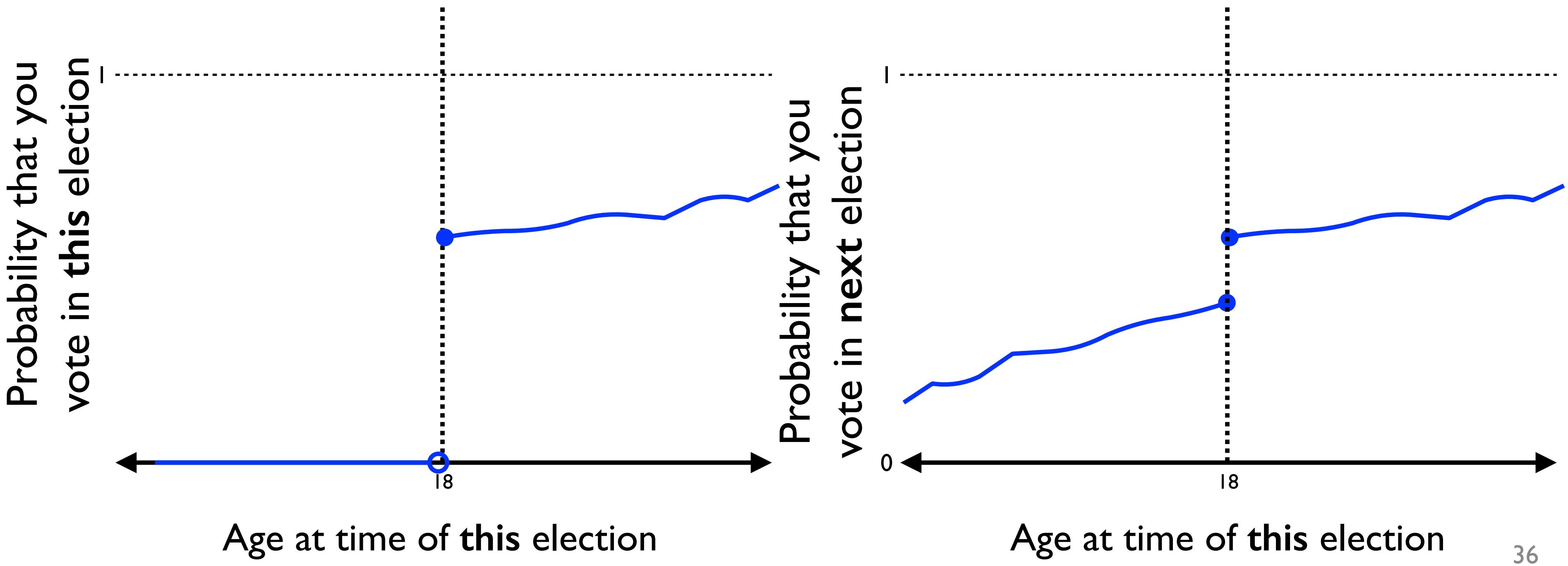

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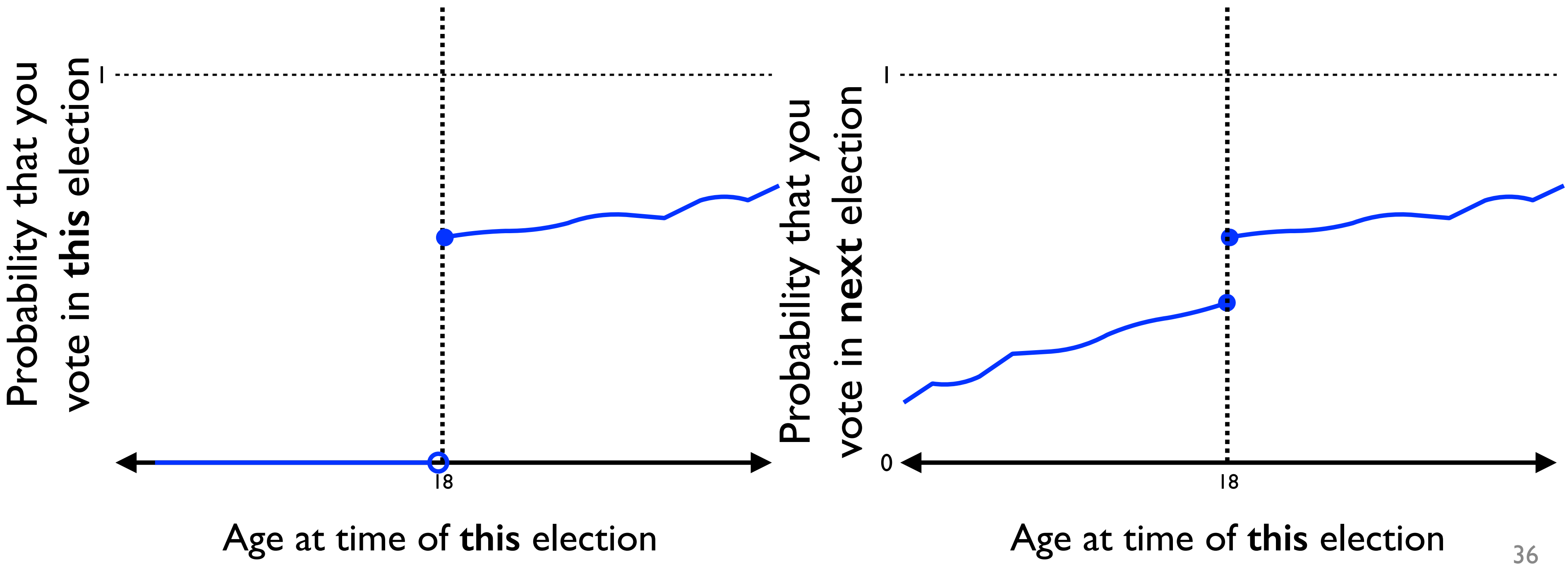
Think of fuzzy RDD as IV and use the Wald estimator:



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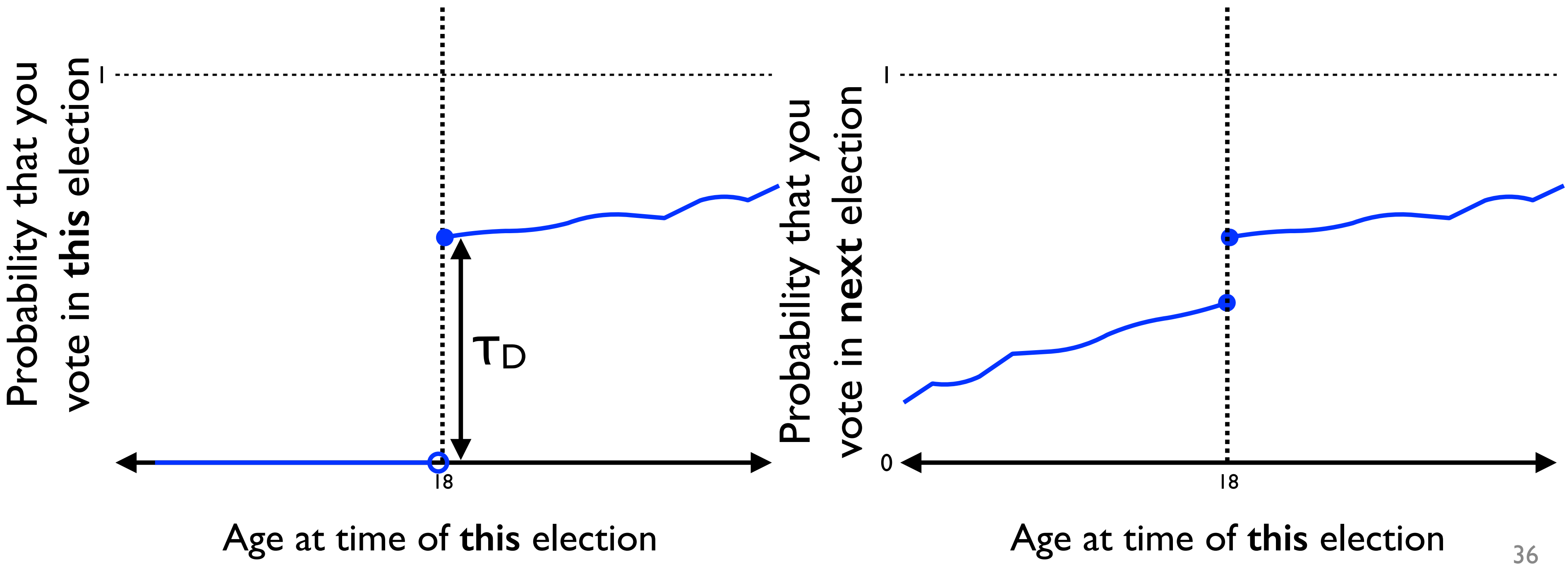

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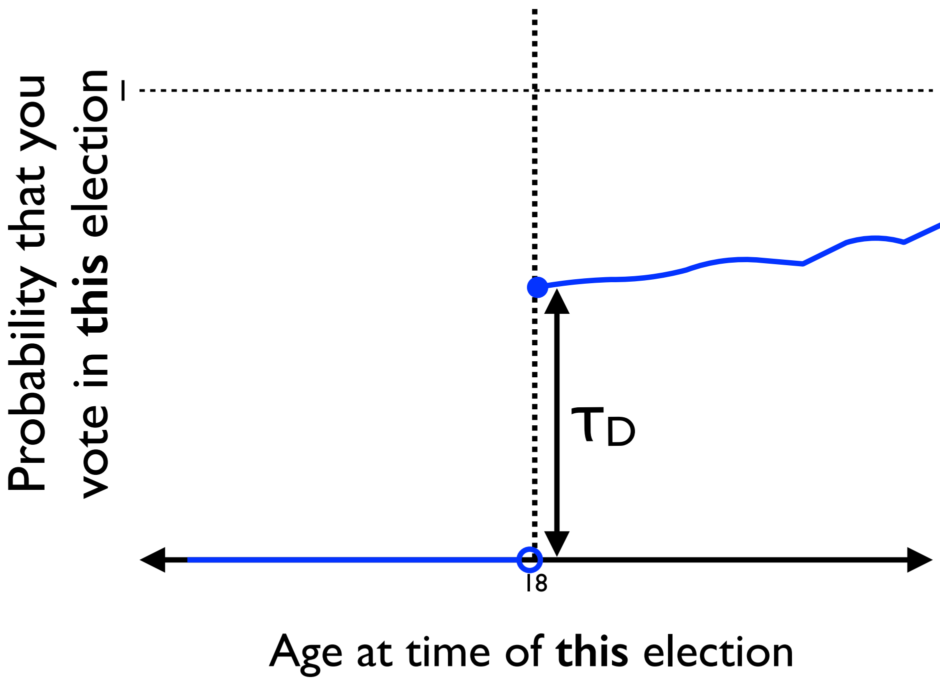

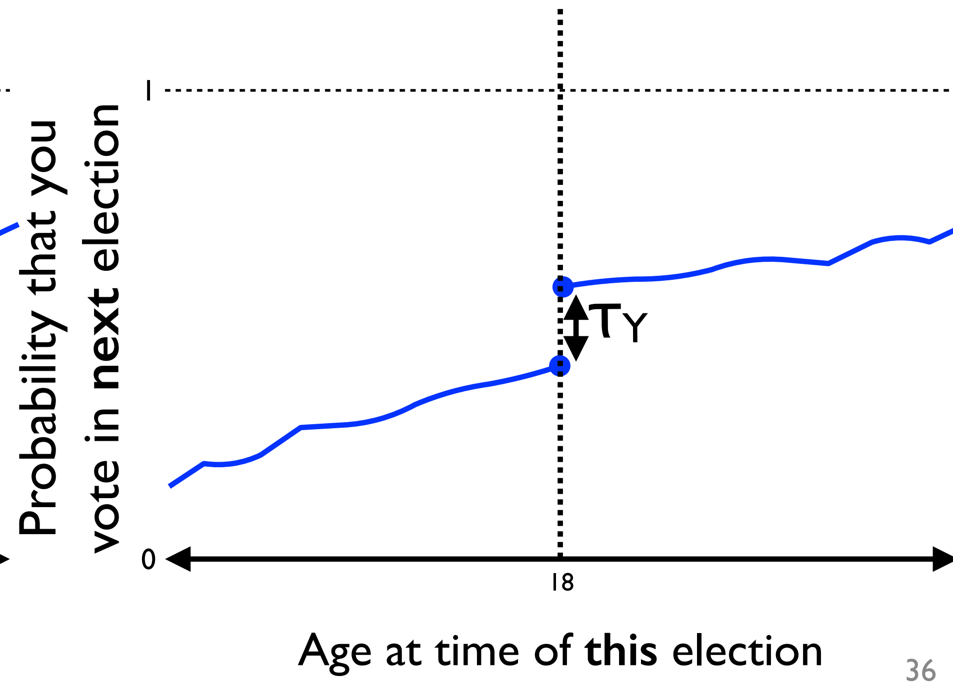

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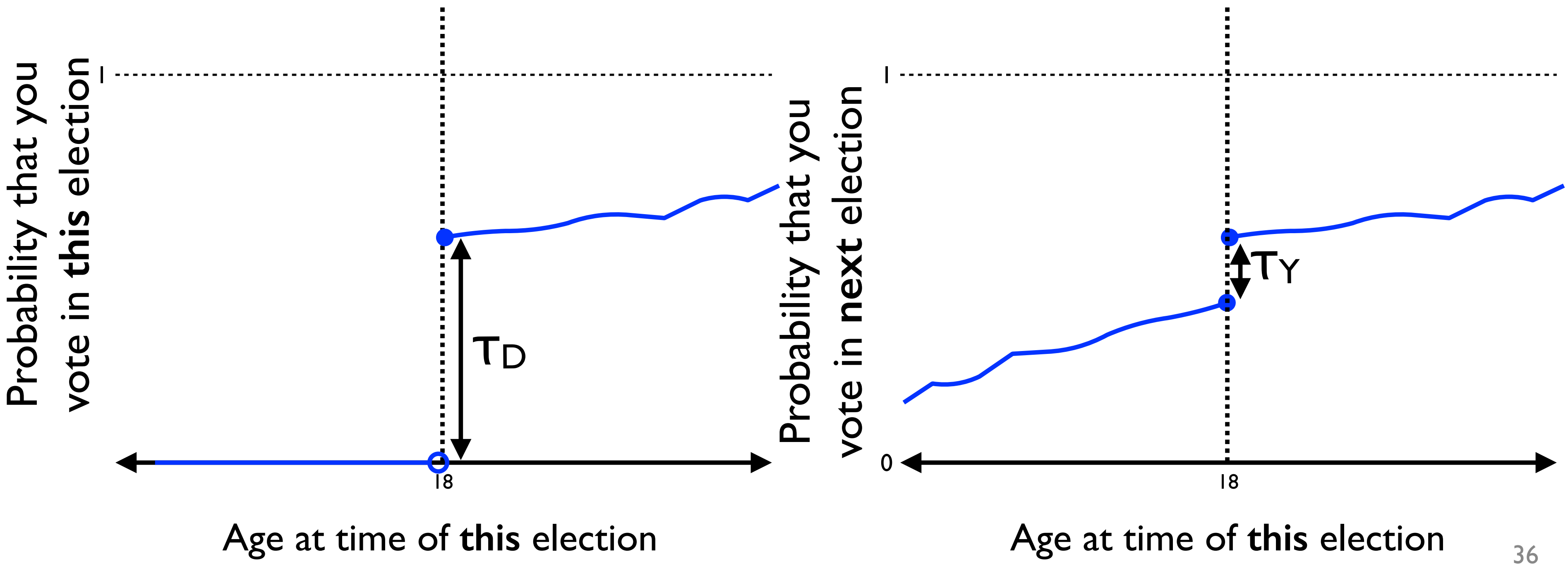

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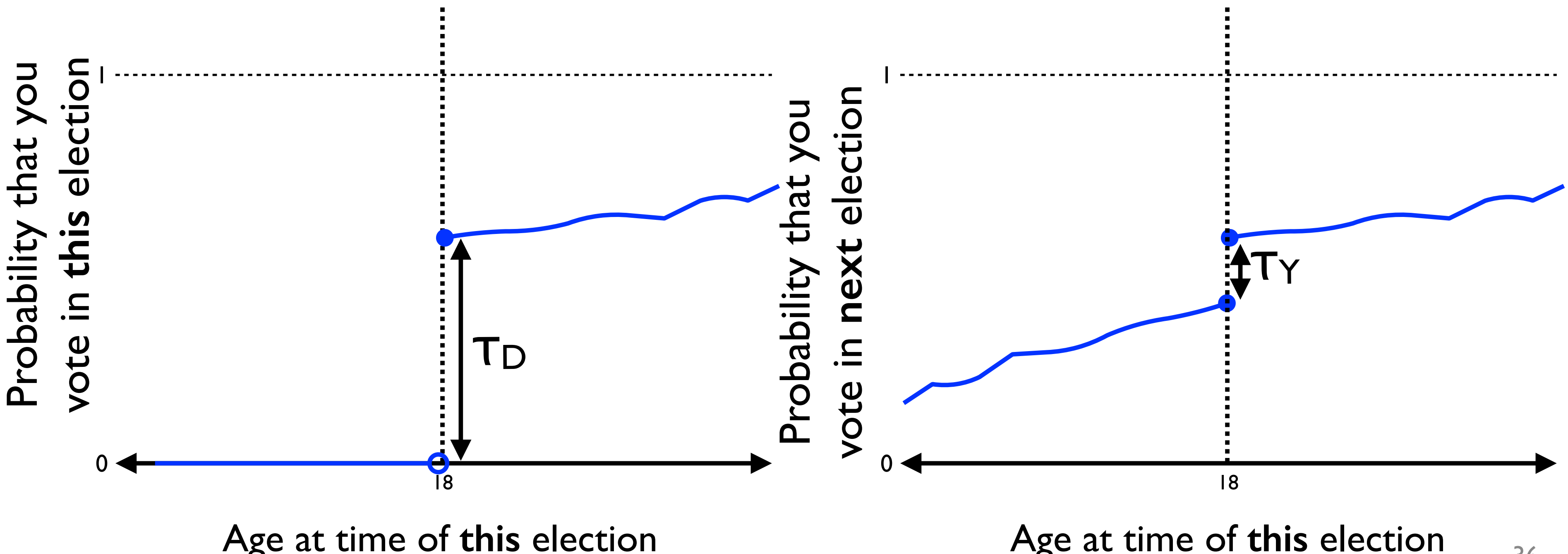

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- Other suggestions?

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You may find other cases where a transparent rule treats similar units differently — keep an eye out!