Lecture 14: Regression discontinuity I

PPHA 34600
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An example: Electricity rebates in California

Policy issue:

- Economists love taxes (to reduce bad stuff)!
- And electricity generation produces bad stuff
- ...but nobody else likes taxes, so policymakers often use rebates instead
- Are these rebates actually effective?

Approach:

- Look at the "20/20" policy in California
- Customers who reduced energy use by 20% received a 20% discount
- Eligibility for the policy isn't random...
- ...but is determined by a policy rule:
- Customers had to have an account before a cutoff date

→ Use a RD model to estimate treatment effects

Estimating the effects of 20/20

Koichiro runs a version of:

$$Y_{it} = \tau D_{it} + f(X_i) + \alpha_i + \delta_t + \varepsilon_{it} \text{ for } c - h \leq X_i \leq c + h$$

where

Y_{it}: energy use by household i in month t

$D_{it} = \mathbf{1}[X_i \leq c] \times [t \in \text{program period}]$

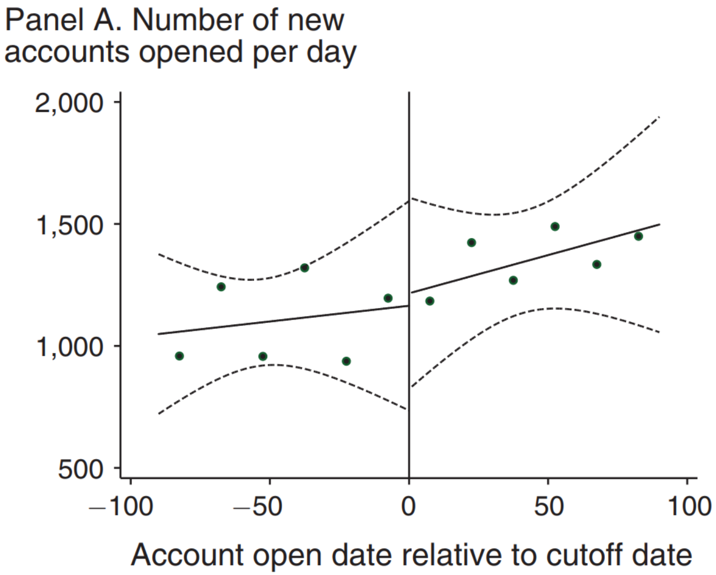
c is a cutoff date by which accounts had to be opened for eligiblity

$f(X_i)$ is a flexible function of the running variable, X_i

α_i, δ_t are customer and time FE, respectively

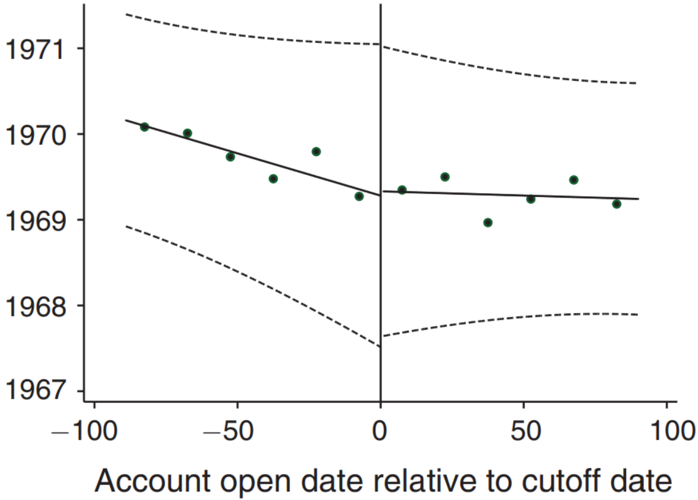
ε_{it} is an error term

Checking the identifying assumption

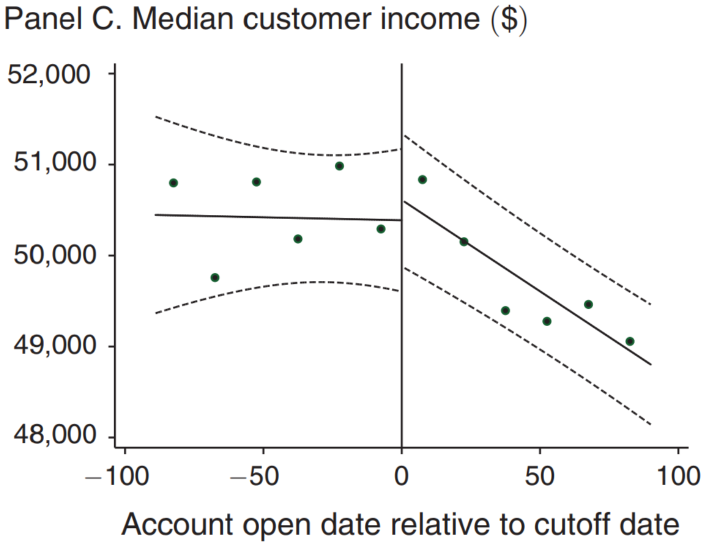


Checking the identifying assumption

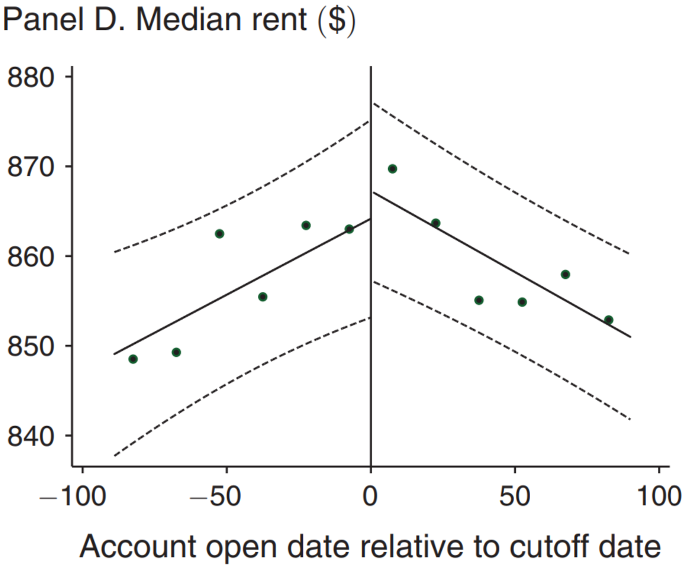
Panel B. Median year structure built



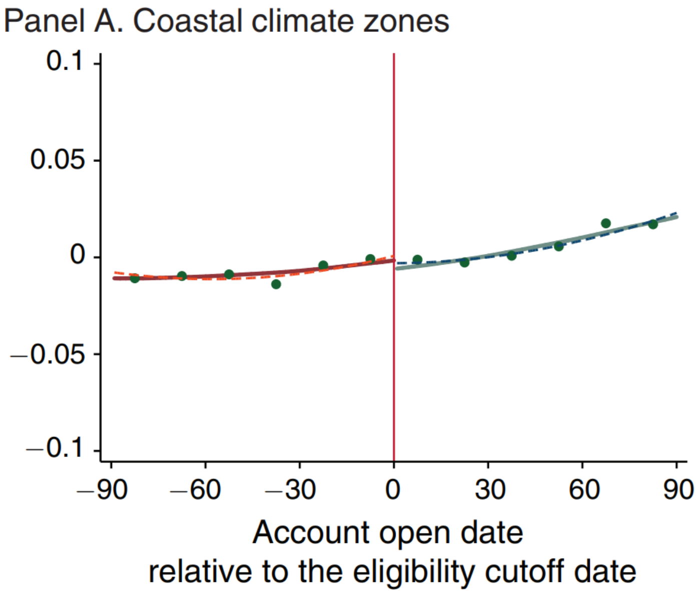
Checking the identifying assumption



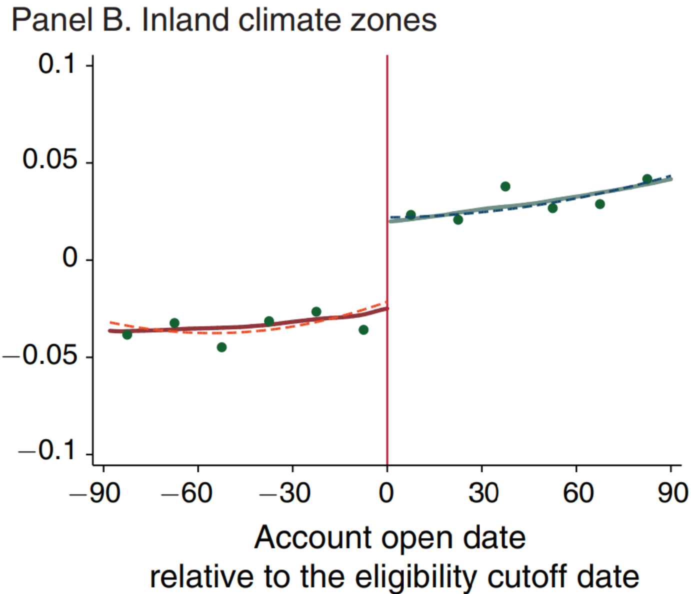
Checking the identifying assumption



Main results



Main results



Bandwidth sensitivities

	Coastal climate zones			Inland climate zones		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect in May	0.004	0.003	0.005	−0.034	−0.039	−0.029
	(0.004)	(0.003)	(0.004)	(0.015)	(0.014)	(0.017)
Treatment effect in June	−0.002	−0.001	−0.003	−0.055	−0.059	−0.05
	(0.004)	(0.004)	(0.004)	(0.017)	(0.016)	(0.019)
Treatment Effect in July	0.004	0.005	0.005	−0.041	−0.039	−0.042
	(0.004)	(0.004)	(0.005)	(0.019)	(0.017)	(0.022)
Treatment effect in August	−0.004	−0.005	−0.003	−0.036	−0.034	−0.035
	(0.004)	(0.004)	(0.004)	(0.018)	(0.016)	(0.020)
Treatment effect in September	−0.005	−0.003	−0.004	−0.056	−0.053	−0.052
	(0.003)	(0.004)	(0.004)	(0.016)	(0.015)	(0.018)
Controls for $f(x)$	Local linear	Quadratic	Quadratic	Local linear	Quadratic	Quadratic
Bandwidth	90 days	120 days	60 days	90 days	120 days	60 days
Observations	2,540,472	3,325,388	1,707,589	208,537	237,264	162,067

Notes: This table shows RD estimates with different bandwidth choices and alternative controls for the running variable. The dependent variable is the log of electricity consumption. The standard errors are clustered at the customer level to adjust for serial correlation.

Cost-effectiveness

Table 8—Program Cost per Estimated Reductions in Consumption and Carbon Dioxide

	Coastal	Inland	Total
Number of customers	3,190,027	299,178	3,489,205
Consumption in summer 2005 (kWh)	8,247,457,920	1,154,292,248	9,401,750,168
Direct program cost for rebate ($)	9,358,919	1,250,621	10,609,540
Estimated reduction (kWh)	9,908,840	50,605,714	60,514,555
Estimated reduction in carbon dioxide (ton)	4,459	22,773	27,232
Program cost per kWh ($/kWh)	0.945	0.025	0.175
Program cost per carbon dioxide ($/ton)	2,099	55	390
Program cost per carbon dioxide ($/ton) (Adjusted for noncarbon external benefits)	2,090	46	381