The Effect of Financial Incentives on Energy Conservation.

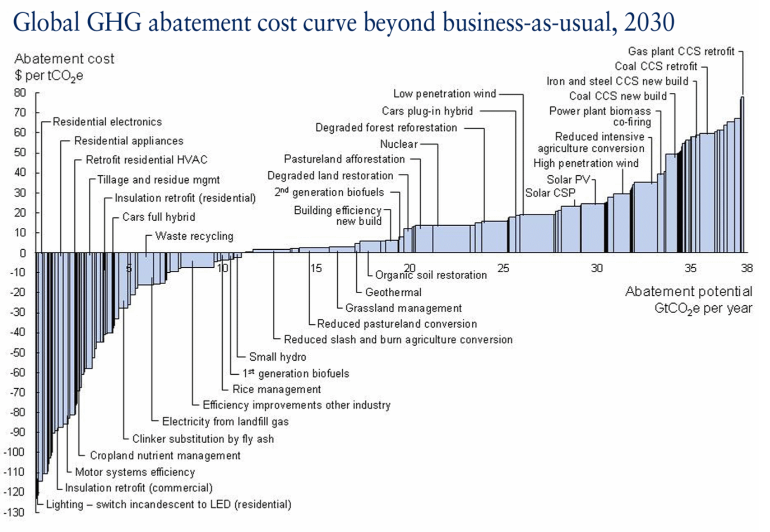
Evidence from a Regression Discontinuity Design in the California 20/20 Rebate Program.

Koichiro Ito (UC Berkeley ARE and UCEI)

Ph.D. Candidate in ARE (Agricultural and Resource Economics) at UC Berkeley
Research Assistant at UCEI (UC Energy Institute)
koichiro@berkeley.edu

Camp Resources 2009

Residential Electricity Sector - The Lowest Abatement Costs?



Source: "Pathway to Low Carbon Economy", Mckinsey & company

Economic Incentives for Households

1. Subsidize energy-efficient homes or appliances.
2. Increase electricity price.
3. Provide further financial incentives to save electricity.

- California 20/20 electricity rebate program (2001, 2002, and 2005)

20% less summer electricity use relative to the previous year

$\Downarrow$

20% discounts for summer month bills

- In 2005, 10% of households in California received rebates (total $67M).
  - Total demand savings by rebated customers were 615,644kWh.
  - But, how much of these savings actually came from "conservation"?

Key Issues and Research Question

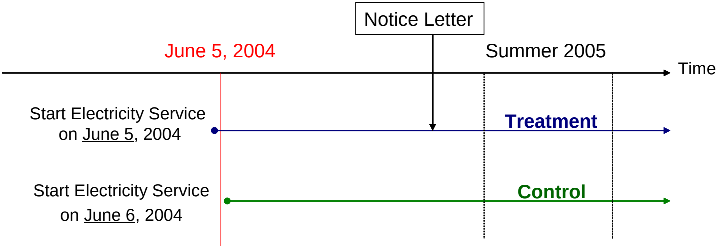
- Some households would receive rebates NOT due to their conservation. Evidence from years with no rebate program:

Year	Weather change	%Change in usage (Median)	%Households with 20% or more reduction
2003-2004	Cooler	-1.7%	14.3%
1999-2000	Hotter	7.7%	6.8%

- Confounding factors in evaluating year-to-year consumption changes:
  - (1) weather; (2) rate changes; (3) other conservation programs; (4) macroeconomic shocks; and (5) household specific events.
- Research question:
  - <u>How to identify the effect induced by the program *itself* ?</u>

Sharp Discontinuity in the Program Eligibility in 2005

- Customers must have started service by a certain cutoff date in 2004.
  - This rule generates essentially random assignment among households who opened their account near the cutoff date.

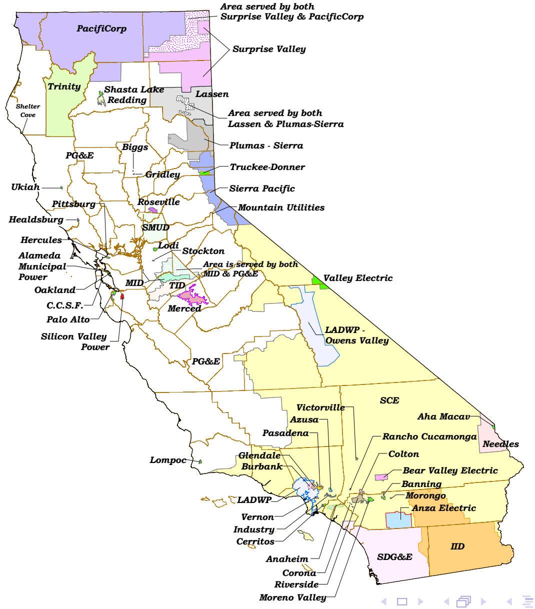


- No self-selection: All eligible customers automatically participated in the program.

Data

- Household-level monthly billing records from the three investor-owned utilities:
  - PG&E (Pacific Gas & Electric)
  - SCE (Southern California Edison)
  - SDG&E (San Diego Gas & Electric)
- Each monthly record includes:
  1. Account ID
  2. ZIP+4 (e.g. 94720-5180)
  3. Climate zone defined by the utilities
  4. Tariff schedules
  5. Billing period (e.g. May15-Jun14)
  6. Electricity consumption (kWh) during the billing period
- Importantly, the data include the exact account start date for each customer.

California
Electric Utility Service Areas



A Sharp Regression Discontinuity Design

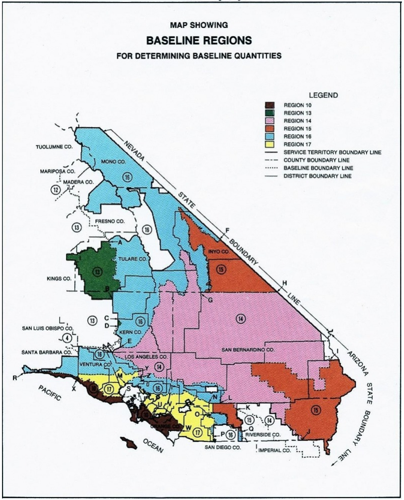
- Estimate the following equation by climate zone for each month separately

$$\Delta ln(y_{i,t}) = \alpha \cdot Treat_i + f(x_i) + \theta_{zip,t} + \delta_{cycle} + \epsilon_{i,t}$$

$y_{i,t}$: *Average daily electricity use for customer i at billing month t*
$\Delta ln(y_{i,t})$: *Difference in log between 2005 and 2004*
x_i : *Account open date*
$Treat_i = 1$ *if* $x_i \leqslant c$, *where* $c =$*the cutoff date to be eligible*

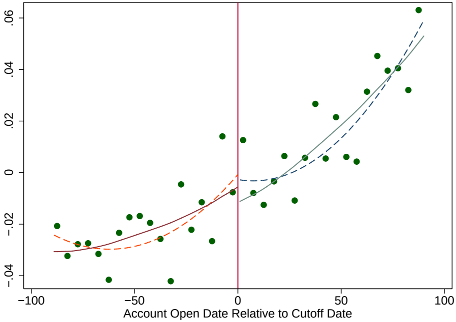
- To deal with $f(x_i)$,
  - Limit observations in narrow windows from the cutoff date.
  - Use flexible parametric function for $f(x_i)$ or
  - Local liner regression with triangular kernel (Imbens and Lemiux 2008)

Southern California Edison (SCE)



SCE Climate Zone 10: Representative Cities (Santa Barbara, Long Beach and Irvine)

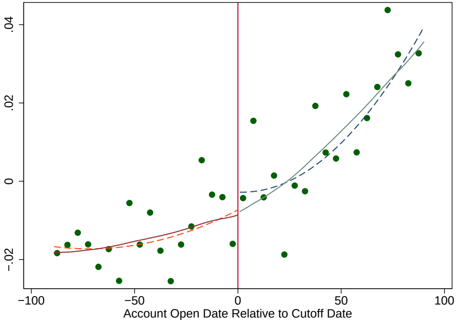
$$\Delta ln(y_{i,t}) \equiv ln(y_{i,Sep2005}) - ln(y_{i,Sep2004})$$



Point estimate (robust standard error):

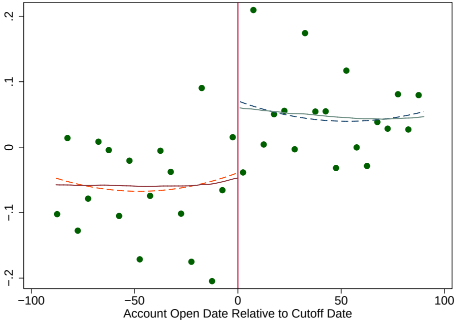
.005 (.007)

SCE Climate Zone 17:Representative Cities (Riverside)



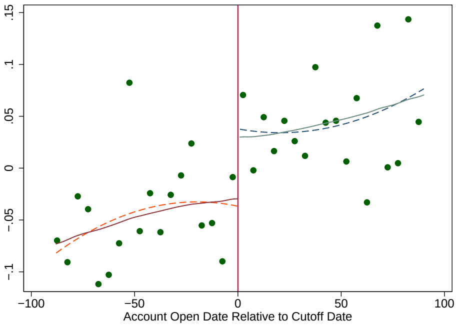
-.002 (.008)

SCE Climate Zone 16: Representative Cities (Bakersfield)



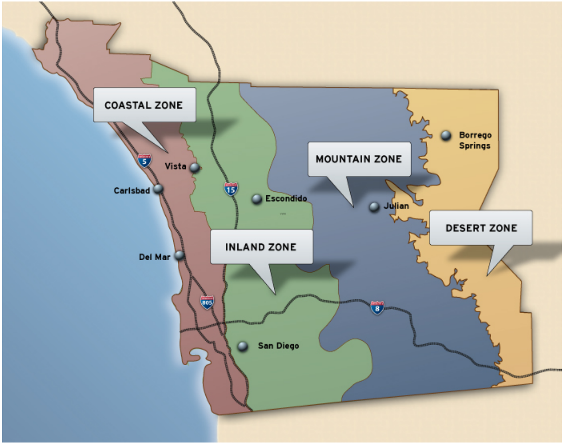
-.093** (.040)

SCE Climate Zone 15: Representative Cities (Palm Dessert, Death Valley)

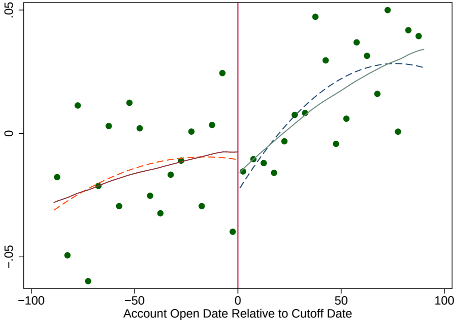


-.091*** (.032)

San Diego Gas&Electric (SDG&E)

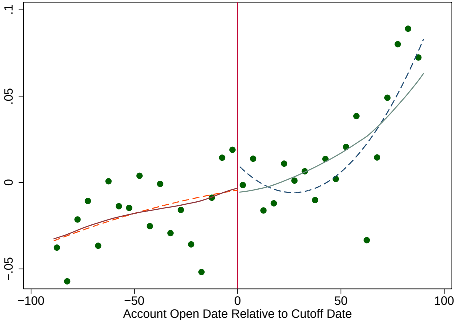


SDG&E Coastal Climate Zone: Representative Cities (Del Mar)



.008 (.011)

SDG&E Inland Climate Zone: Representative Cities (San Diego)



.003 (.013)

Estimates for Each Month

PG&E	6	7	8	9
Coastal	-.002	-.001	.003	-.002
	(.004)	(.003)	(.004)	(.005)
Inland	-.009	-.016*	-.032***	-.059***
	(.013)	(.011)	(.011)	(.012)

SCE	6	7	8	9
Coastal	.001	-.001	-.001	-.002
	(.009)	(.010)	(.009)	(.008)
Inland	-.019*	-.032**	-.056***	-.092***
	(.015)	(.016)	(.016)	(.015)

SDG&E	7	8	9	10
Coastal	.005	-.001	-.002	.008
	(.009)	(.010)	(.009)	(.011)
Mid-Inland	-.002	-.001	.002	.003
	(.011)	(.012)	(.011)	(.013)

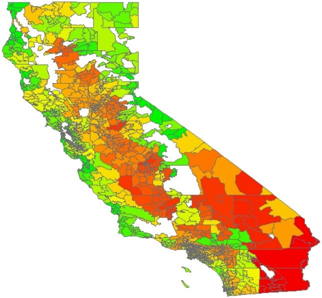
Summary of Results and Implications

(1) Coastal areas: Virtually no treatment effect

(2) Inland areas: 5-10% average treatment effect

- Summer temperature is persistently high in the inland areas.
- Use of air conditioner is likely to drive these heterogeneous treatment effects.

Cooling Degree Days



Summary of Results and Implications

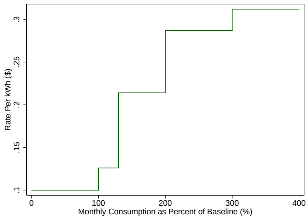
(3) The overall cost-effectiveness is lower than publicly announced because:

- The program has little effect on the heavily populated coastal areas although it has an effect in the inland areas.
- The households in the coastal areas still received rebates due to the year-to-year fluctuation in consumption.

(4) The treatment effects are smallest in the 1st month and increasing toward the last month.

Further Issues

1. The effect of the incentive scheme on dynamic behavior:
   - The results show larger average treatment effects in the last month.
   - Some customers may have large incentives in the last month while others have almost zero incentive.
   - Duflo, Hana, and Ryan (2008): Incentives for teacher attendance
2. Treatment effect under nonlinear pricing:
   - Customers on the higher tiers may have larger incentives.



End of Presentation

Thank you.

(BackUpSlide) Treatment and Control Groups in Pre-Treatment

- $\ln(y)$ in September 2004 (controlled for zip level fixed effects)
  - Each dot represents 5 days local mean
  - Downward trend, but continuous at the cutoff date.