Asymmetric Incentives in Subsidies:

Evidence from a Large-Scale Electricity Rebate Program

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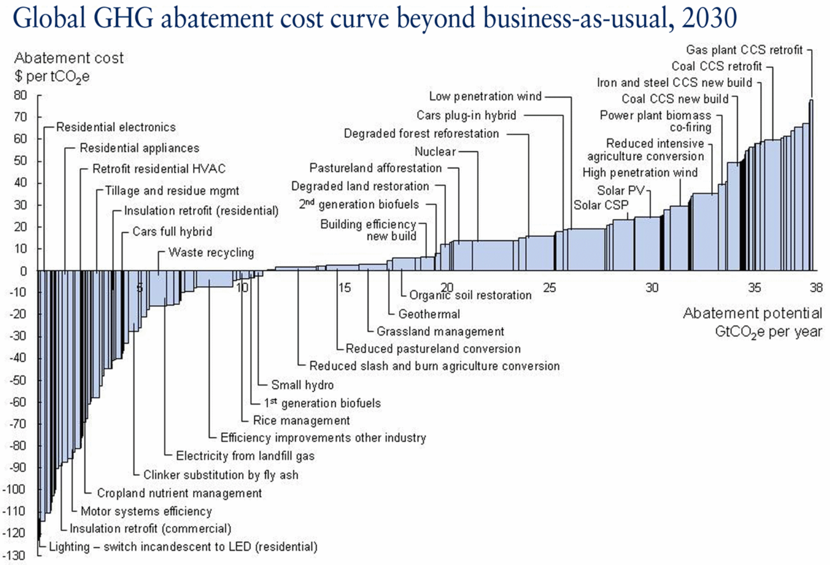
Residential Electricity Sector - The Lowest Abatement Cost?



Economists are usually skeptical about this optimistic view

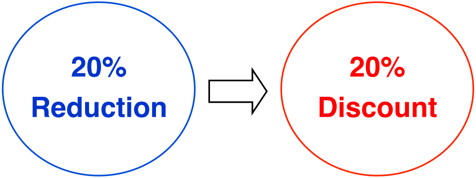
- Price elasticity of residential electricity demand is small
- A significant price increase is often politically infeasible
- What can we do?

California's state-wide "20/20 Electricity Rebate Program" in 2005

Reduce 20% of your electricity use during the four summer months
(relative to your usage in 2004)

$\Downarrow$

Get a 20% discount for all of the four summer month bills in 2005



- Policy objective: Lower electricity use in the summer of 2005
- No application was required
- Virtually all California households participated

I examine whether the program achieved its policy goal

Policy goal:

- Encourage households to reduce summer electricity consumption

Research questions:

1. How much electricity was saved because of the program?
2. What was the program's cost-effectiveness?

Why do we care about the questions?

Reason (1) A large scale program with a significant expense

- The summer four billing months in 2005

Utility	Revenue ($M)	Rebated Households	Rebate ($M)
PG&E	1,322	8.24%	10.79
SCE	1,257	7.91%	10.61
SDG&E	363	9.07%	4.33

- The rebate expense was close to 1% of each utility's revenue
- The expense was eventually paid by ratepayers

Reason (2) Similar programs are widely used to promote conservation

Similar Rebate Programs in California:

- Summer electricity 20/20 rebate program in 2001 and 2002 (Reiss and White 2008)
- Winter gas rebate program in every year in PG&E

Peak-Time Rebate Program:

- Anaheim (Wolak 2006)
- Washington DC (Wolak 2011)
- Many other electric utilities in the US and other countries

Reason (3) However, the cost-effectiveness has been controversial

Critique:

- Many households may get rebates without conservation efforts
- Example 1: If they get milder weather in the target year
- Example 2: If they had a visitor in the base year

Evidence from years that did not have a rebate program:

Year	Weather	%Households with 20% or more reduction
2003 to 2004	Cooler in 2004	14.3%
1999 to 2000	Warmer in 2000	6.8%

How to identify the causal effect of the program?

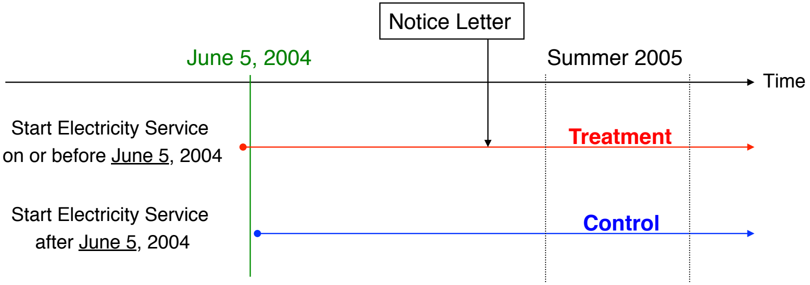
Household electricity consumption can be affected by:

1. Weather
2. Macro economic shocks
3. Electricity prices
4. The treatment effect of the program
5. Other conservation campaigns

The key question is how to disentangle (4) from others

I use the program's eligibility rule to estimate the treatment effect

- **Eligibility rule**: Households must be at the same premise since a certain cutoff date in 2004



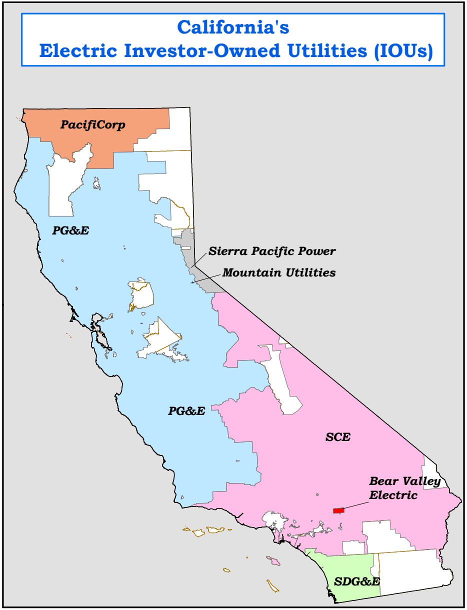
- The program has not been announced until the spring of 2005

Road Map

1. Introduction
2. Data
3. Identification Strategy
4. Result
5. Conclusion

Data: Household-level Monthly Billing Records

- Household-level monthly billing records
  1. PG&E (Pacific Gas & Electric)
  2. SCE (Southern California Edison)
  3. SDG&E (San Diego Gas & Electric)
- Each monthly record includes:
  1. Account ID
  2. Nine-digit ZIP code (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
  7. Account start date and close date

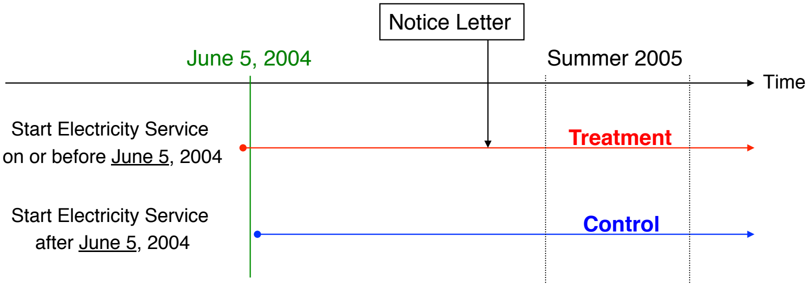

California's
Electric Investor-Owned Utilities (IOUs)
PacifiCorp
PG&E
Sierra Pacific Power
Mountain Utilities
PG&E
SCE
Bear Valley
Electric
SDG&E

Data: Weather and Demographic Data

- Weather data from the Cooperative Station Dataset by NOAA
  - Daily data at the weather station level
  - Daily max and min temperature
- Demographic data from the US Census in 2000
  - At the Census Block Group (CBG) level
  - Median household income

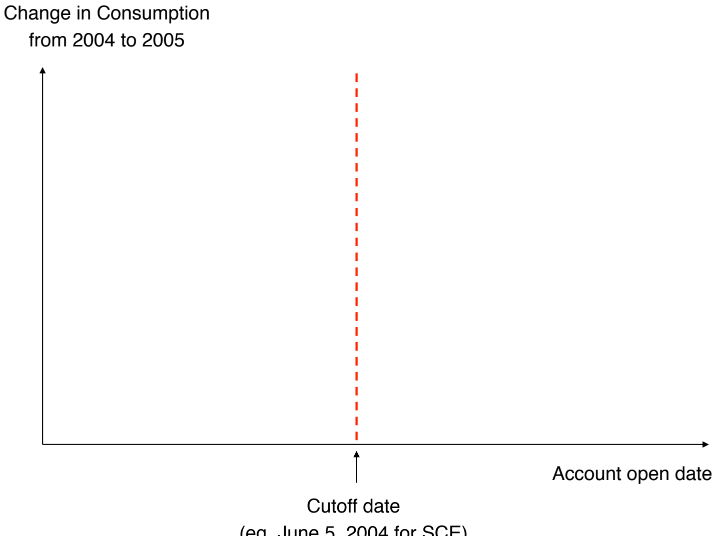
Identification Strategy

I compare electricity consumption between treatment and control groups



1. Essentially random assignment of the treatment across the cutoff
2. No strategic entering b/c the program cannot be anticipated in 2005
3. No self-selection b/c all eligible households automatically enrolled

I compare electricity consumption between treatment and control groups



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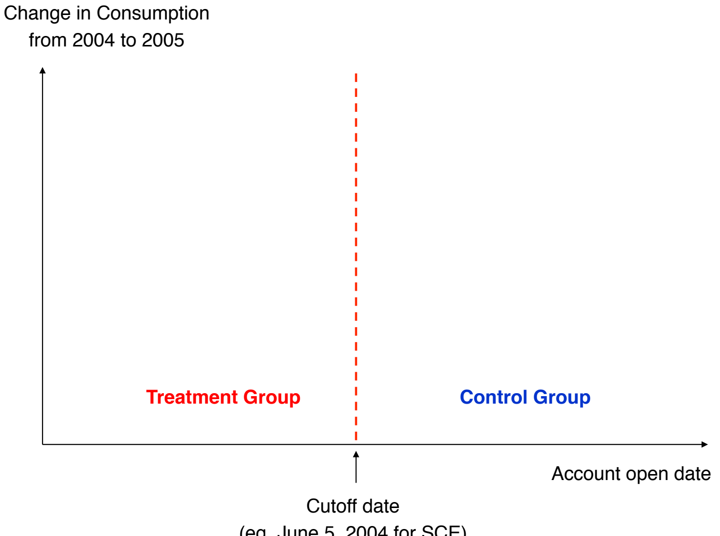

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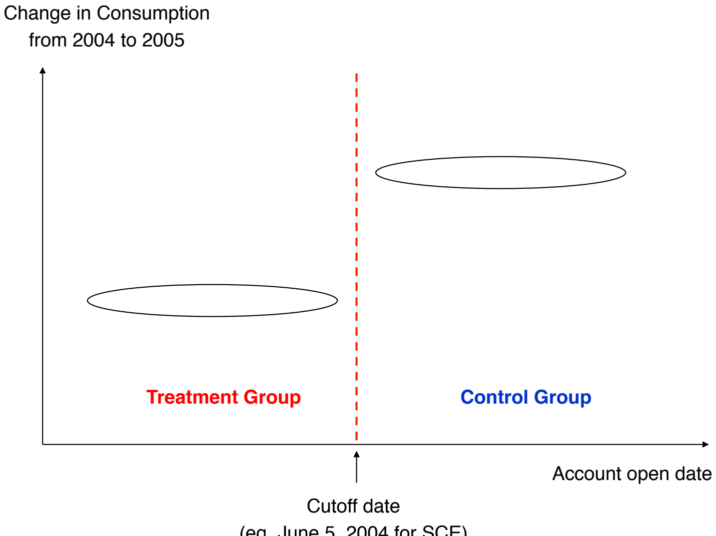
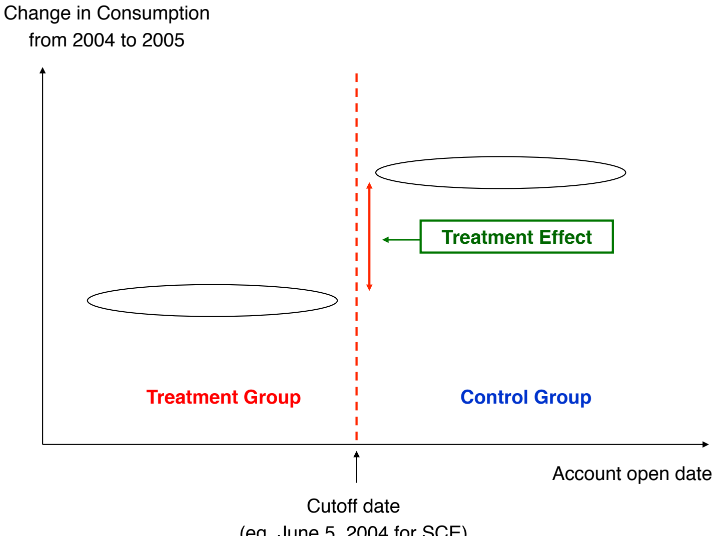


I compare electricity consumption between treatment and control groups



Estimation: A Regression Discontinuity Design with a sharp discontinuity

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

- $y_{i,t}$ = household i's electricity consumption in billing period t
- $\Delta \ln(y_{i,t}) =$ differences in log between the same month of 2005 and 2004
- x_i = service start date
- $Treat_i = 1$ if $x_i \leq c$, where $c =$ the cutoff date to be eligible
- To control for $f(x_i)$
  - Limit observations in narrow windows from the cutoff date
  - Use flexible parametric function for $f(x_i)$ or
  - Local liner regressions (Imbens and Lemieux 2008)

Parametric and Nonparametric Controls

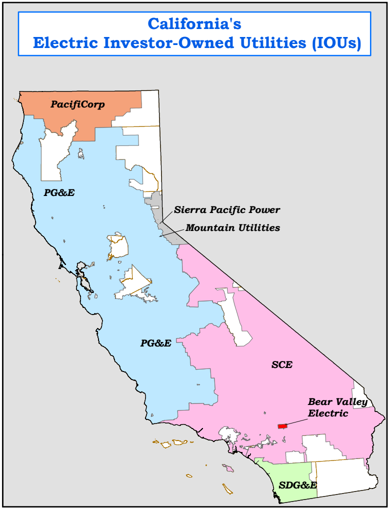
- **Method 1**: Include a flexible parametric function of X_i:

$$\triangle \ln y_{it} = \alpha + \beta \cdot Treat_i + \sum_{s=1}^{S} (\gamma^s \cdot X_i^s + \theta^s \cdot Treat_i \cdot X_i^s) + \delta_{zip} + \delta_{cycle} + \varepsilon_{i,t}$$

- **Method 2**: Non-parametrically control for X_i by the local linear regression using a triangular kernel (Imbens and Lemieux 2008)

$$\triangle \ln y_{it} = K\left(\frac{X_i - c}{h}\right) \cdot (\alpha + \beta \cdot Treat_i + \gamma \cdot X_i + \theta \cdot Treat_i \cdot X_i + \delta_{zip} + \delta_{cycle} + \varepsilon_{i,t})$$

Estimation Results for Southern California Edison (SCE)



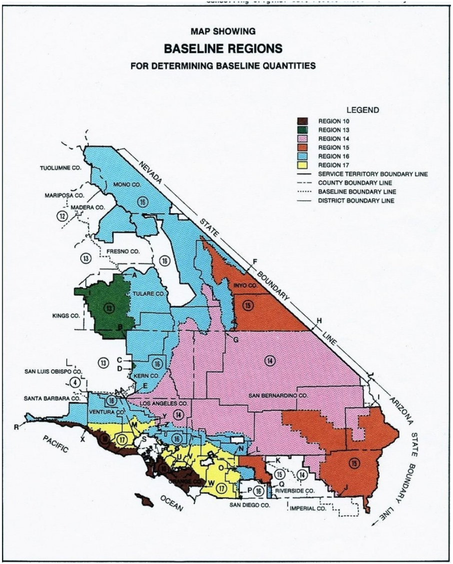
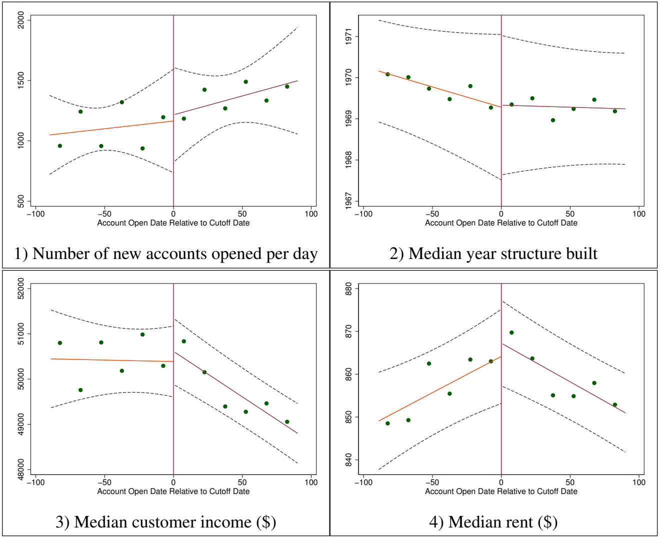


Figure 2: Testing the Validity of the Regression Discontinuity Design



1) Number of new accounts opened per day

2) Median year structure built

3) Median customer income ($)

4) Median rent ($)

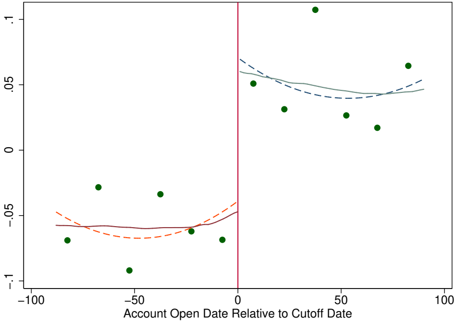
Note: The horizontal axis shows the account open date relative to the cutoff date of the program eligibility, which was June 5, 2004. Each dot shows the local mean with a 15-day bandwidth. The solid line shows the local linear fit and the dashed lines present the 95 percent confidence intervals. The confidence intervals for the fitted lines for variables from Census data are adjusted for clustering at the census block group level.

SCE Climate Zone 16: Representative Cities (Bakersfield)

- Dependent variable:

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

- **Dot**: Local average using fifteen days windows
- **Solid line**: Local linear regression
- **Dashed line**: Parametric regression
- Zip code dummy and billing cycle dummy are included



Point estimate (robust standard error):

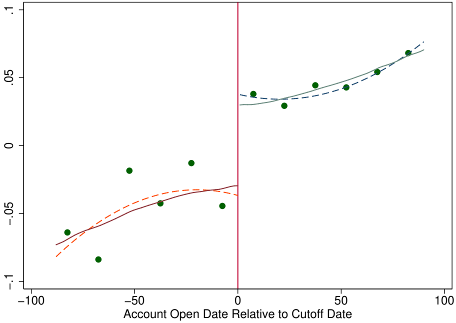
-.101** (.032)

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

- Dependent variable:

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

- **Dot**: Local average using fifteen days windows
- **Solid line**: Local linear regression
- **Dashed line**: Parametric regression
- Zip code dummy and billing cycle dummy are included



Point estimate (robust standard error):

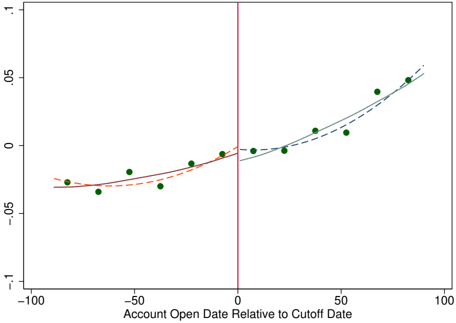
-.091*** (.040)

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

- Dependent variable:

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

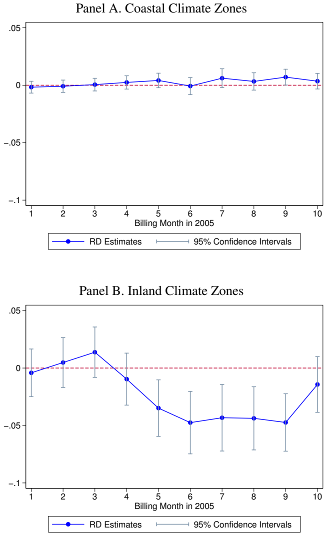
- **Dot**: Local average using fifteen days windows
- **Solid line**: Local linear regression
- **Dashed line**: Parametric regression
- Zip code dummy and billing cycle dummy are included



Point estimate (robust standard error):

.005 (.007)

Figure 4: The Difference in Log Consumption between Treatment and Control Groups



Note: This figure presents the RD estimates of the difference in log consumption between the treatment and control groups. Customer fixed effects are subtracted by using consumption data before January 2005. I use a 90-day bandwidth and quadratic controls for the trend of the running variable, which is the same specification used to obtain my main estimation results shown in Table 2.

Table 2: RD Estimates of the Effect of Rebate Incentives on Energy Conservation

	Coastal Climate Zones		Inland Climate Zones	
	(1)	(2)	(3)	(4)
Treatment Effect	-0.001		-0.042	
	(0.002)		(0.013)	
Treatment Effect in May		0.003		-0.034
		(0.003)		(0.015)
Treatment Effect in June		-0.001		-0.055
		(0.003)		(0.017)
Treatment Effect in July		0.004		-0.041
		(0.004)		(0.019)
Treatment Effect in August		-0.003		-0.037
		(0.004)		(0.018)
Treatment Effect in Septermber		-0.004		-0.056
		(0.003)		(0.016)
Observations	2,540,472	2,540,472	208,537	208,537

Note: This table shows the RD estimates of the effect of rebate incentives on energy conservation. The dependent variable is the log of electricity consumption. I estimate equation (2) with a 90-day bandwidth and quadratic functions to controls for the running variable. The standard errors are clustered at the customer level to adjust for serial correlation.

Table 3: Robustness Checks: Alternative Bandwidths and Specifications

	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 Septermber	-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	Quradratic	Local linear	Quadratic	Quradratic
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

Note: 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.

Table 6: Potential Long-run Effects

	Coastal				Inland			
	2005	2006	2007	2008	2005	2006	2007	2008
Treatment Effect	-0.001	0.001	-0.002	0.002	-0.042	-0.040	-0.048	-0.043
	(0.002)	(0.003)	(0.004)	(0.004)	(0.013)	(0.018)	(0.021)	(0.022)

Note: This table shows the RD estimates of the potential long run effect of rebate incentives on energy conservation. The dependent variable is the log of electricity consumption. The treatment variable is the interaction of the treatment group and the summer of 2006, 2007, and 2008, which are one, two, and three years after the rebate program. The standard errors are clustered at the customer level to adjust for serial correlation.

What Drives Heterogeneous Treatment Effects?

At least two possible reasons:

1. Climate conditions (air conditioner usage)
2. Income levels

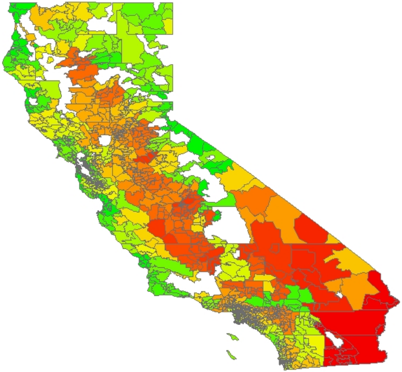


Table 4: RD Estimates Interacted with Income, Climate, and Air Conditioner Saturation

	(1)	(2)	(3)	(4)
Treatment	0.095	-0.297	-0.199	-0.478
	(0.051)	(0.055)	(0.077)	(0.056)
Treatment*Ave.Temp.(F)	-0.0015		-0.0016	
	(0.0007)		(0.0008)	
Treatment*ln(Income)		0.029	0.031	0.044
		(0.005)	(0.005)	(0.003)
Treatment*Air Conditionar				-0.014
				(0.005)
Observations	2,749,009	2,749,009	2,749,009	2,749,009

Note: This table presents the RD estimates of the effect of rebate incentives on energy conservation interacted with income, climate conditions, and air conditioner saturation. The dependent variable is the log of electricity consumption. I use a 90-day bandwidth and quadratic controls for the trend in the running variable. Income is at the census block group level. Average temperature and air conditioner saturation (the ratio of customers who own air conditioners) are at the five-digit zip code level. The standard errors are clustered at the customer level to adjust for serial correlation.

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 non-carbon external benefits)	2,090	46	381

Note: This table reports the cost-benefit analysis of the 20/20 program for SCE's coastal areas, inland areas, and all service areas. Row 1 shows the number of residential customers who maintained their accounts in the summer of 2004 and 2005. Row 2 presents the aggregate consumption in the summer months. Row 3 reports the aggregate amount of rebate paid to customers. Row 4 shows the estimated kWh reduction from the treatment effect of the program. Row 5 translates this reduction into the reduction in carbon emissions by using the average carbon intensity of electricity consumed in California, which is 0.9 lb. per kWh according to California Air Resources Board (2011).

Summary

This paper uses a RDD to estimate the effect of the state-wide conservation rebate program in California

- 5 to 10% of consumption reductions in inland areas
- Virtually no effect in most of the coastal areas
- Higher temperature areas → Larger treatment effects
- Lower income areas → Larger treatment effects

Cost-effectiveness:

- Inland areas: 2.5 cents per kWh reduction
- Coastal areas: 94.5 cents per kWh reduction

Policy Implications

- Under the current rebating scheme, many households receive rebates for reasons unrelated to their conservation efforts
- The cost-effectiveness would be very poor if the treatment effect is not sufficiently large (e.g. the findings for the coastal areas)
- Focusing on households with lower income and warmer climate areas may improve the cost-effectiveness

Thank you

- Thank you for your attention!