Carnegie Mellon University

Smart Rebates: Targeting High-Value Energy Efficiency Improvements with Smart-Meter Data

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Two-Fold Research Approach



- First, which households are most likely to participate in utility-sponsored energy efficiency (or load management) programs?
 - Can we inform program marketing efforts target the households most likely to be receptive to these programs?
- Second, what is the realized energy effect of utilitysponsored energy efficiency programs?
 - With high frequency Smart Meter energy readings, we can look at both the *quantity* of energy savings and the *value* of that savings, based on time-varying marginal cost of production.
- Combining these we can ask; from which households should the demand-side program operator expect to create the most valuable energy savings?

CEDM

The Data (1 of 2)

- PG&E sample of SmartMeter households from the period of 2009-2011
 - About 10,000 households from each of three major climate zones in their service territory for ≈ 30,000 households.
 - 15 minute and daily energy readings for each household.
 - Participation in utility-sponsored energy efficiency and load management programs recorded.
- PG&E started installing Smart Meters in California in 2008, with a gradual roll-out that continues.
 - This data is sample from over 5 million households in PG&E's territory
 - Most households in the sample did NOT have a Smart Meter at the start of the time period.

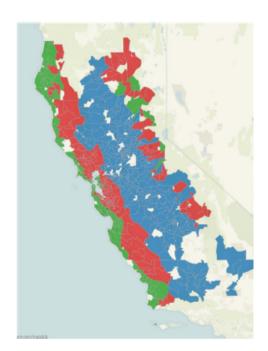




THREE DISTINCT CLIMATE AREAS

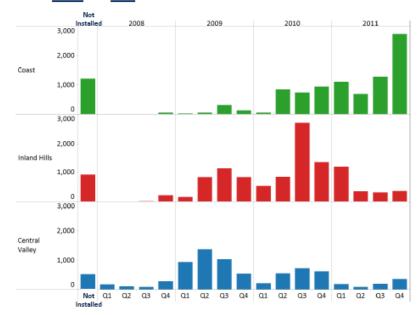
White areas may include areas not covered by data set.

	Locations
Coast	10,555
Inland Hills	12,083
Central Valley	12,424
Total	35,062



SMARTMETERS: ELECTRIC INSTALLATIONS

Variation in when and who received SmartMeters



Figures from WCAI presentation, October 2012

The Data (2 of 2)



- Complement energy readings with neighborhoodlevel demographic data from US Census
 - PG&E included Census blockgroup numbers as household geographic identifiers (addresses withheld for privacy)
 - Can associate neighborhood (≈600 households)
 characteristics with each household.
- Daily weather data from NOAA
 - Each blockgroup matched with the 3 nearest weather stations and an average of the high and low daily temperatures are calculated.
 - Generate degree-day-"like" values by subtracting 20°C from high (with zero bound) and subtracting low from 20°C (also with zero bound)

Background on PG&E's Residential Efficiency Rebates Program



- Rebate program available over the period of the study (and before).
- Households can apply for a rebate following the purchase of energy consuming equipment that meets defined efficiency criteria.
- Households apply for a rebate online, or using a mail in form.

	Rebate Code	Product	Catalog Page #	Install Date	Product Information	Quan Installe		Rebate per Unit (B)	RebateTotal (A x B)
	B34	High Eff. Clothes Washer	1		Manufacturer				
	204	CEE Tier 3, MEF ≥ 2.2, WF ≤ 4.5	'		Model #	u	ınit(s)	\$50 per unit	\$
	DWU3	High Eff. Dishwasher	1		Manufacturer				
		≤ 324 kWh/yr., ≤ 5.8 gal/cycle			Model #	u	nit(s)	\$30 per unit	\$
	DW06	Super High Eff. Dishwasher	1		Manufacturer				
es		≤307 kWh/yr., ≤5.0 gal/cycle			Model #	u	nit(s)	\$50 per unit	\$
Appliance	H169	ENERGY STAR® Room	1		Manufacturer				
pli		Air Conditioner			Model #	u	nit(s)	\$50 per unit	\$
Αp	H722	Natural Gas Tank Water Heater	2		Manufacturer				
		Level 1 (EF = 0.62 to 0.64)			Model #	u	nit(s)	\$30 per unit	\$
	H721	Natural Gas Tank Water Heater	2		Manufacturer				
		Level 2 (EF ≥ 0.65)			Model #	u	nit(s)	\$50 per unit	\$
	H154	Electric Storage Water Heater			Manufacturer			-	
	11134	EF ≥ 0.93	2		Model #	u	nit(s)	\$30 per unit	\$

Program Participation – Single Variable Grouped t-tests



Neighborhood Characteristics for Households that Participate in the Efficiency Rebate Program

(Census Blockgroups ≈ 600 households)

Variable	Difference In Means	t score
Median Home Value*	\$82k (20%)	17
Median Income*	\$16K (20%)	24
% Renters	-13 points (30%)	25
% Poor	-4 points (30%)	16
% w/ Bachelors (or >)	6 points (15%)	13

^{*} These values are top coded (\$1M & \$250k) so difference value reported should be interpreted with caution

Program Participation – Single Variable Grouped t-tests



Energy Characteristics for Households that Participate in the Efficiency Rebate Program

Variable	Difference In Means	t score
Average Daily kWh	17 (25%)	17
Average Weekday kWh	17 (25%)	17
Average Weekend kWh	18 (25%)	18

^{*} Excluding households reporting >1,000kWh/daily on average (7)

Program Participation – Probit Probability Estimation



Variable	Coefficient Estimate (β)			
Average Daily kWh	1.93x10 ⁻³ *			
Median Home Value	4.35x10 ⁻⁷ *			
Median Income	4.13x10 ⁻⁷			
% Renters	-7.91x10 ⁻³ *			
% Poor	-7.93x10 ⁻⁴			
% w/ Bachelors (or >)	5.32x10 ⁻²			
Intercept	-1.44*			
(pseudo) R ²	0.0498			

- Direction of these effects consistent with expectations from univariate ttests
- Cannot interpret these coefficients directly (due to functional form)
- Sign and significance of coefficients robust to alternate model functional forms (logit, tobit, linear)

^{*} denotes statistical significance at >99%





 How can DSM operators get smart about marketing and deploying residential efficiency programs?

- Have a model for program participation
- Next, what is are the energy effects once a household has participated?

Estimating Effect Size – Daily kWh Consumed

CEDM

Coefficient



Time Fixed-Effects Model

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- First rebate is pointing in the wrong direction?
- Subsequent rebates lead to energy savings.
- This is an average effect (across seasons, time since rebate, etc.)
- Interpretation?
 - Consuming more energy services? Free-riders? New homeowners?

Variable	Estimate (β)
Daily High Temp	0.551
Daily Low Temp	0.083
% Renter Occupied	-0.222
% Poor	0.120
Median Home Value	-8x10 ⁻⁶
Median Income	2x10 ⁻⁴
Rebate (1st)	4.476
Rebate (2 nd)	-1.766
Rebate (3 rd)	-2.006
Rebate (4 th)	-8.542
intercept	51.365
Adj R²	0.1402
Temperature measured in te	enths of degrees C

All coefficients statistically significant at >99%

Next Steps



- We've found an interesting daily average effect, but the smart-meters let us do more.
 - Are there interesting energy effects once we drill down to more narrow time slices?
 - Can we detect a change in the relationship between temperature and 15min energy demand?
 - Are there ways to segment households to identify the ones with energy reductions post-intervention?
- Are there ways to cluster households by energy consumption patterns that can help predict program participation?





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