Do Smart Technologies Deliver? Smart Thermostats and Energy Conservation

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Background

- Private costs
  - Average US household uses 166.3 million BTU of energy / year (EIA, 2019a)
  - ~$2,200 in energy bills / year (EIA, 2018)

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- Social costs
  - Residential energy use produces 1 billion metric tons of CO_2 / year (EIA, 2019b)
  - ~20% of all US carbon pollution

Technological Innovation

- Largest share of residential energy (~40%) goes to heating & cooling (EIA, 2019a)

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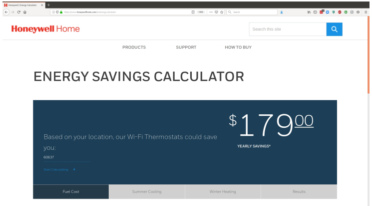
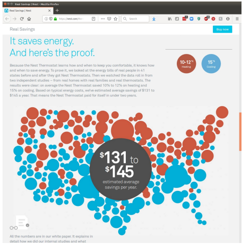
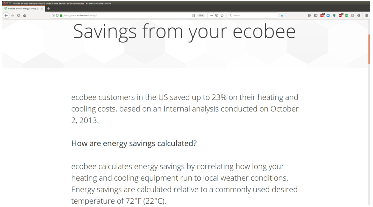
- $\Rightarrow$ Traditional $\rightarrow$ smart thermostat

Big Savings!?!







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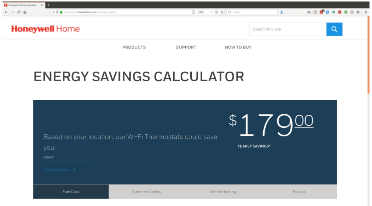

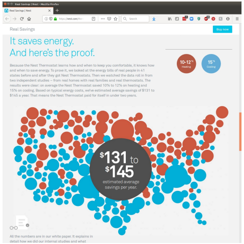

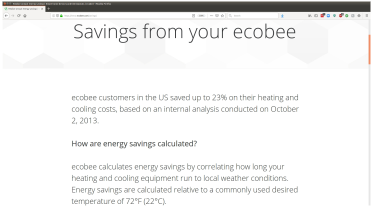

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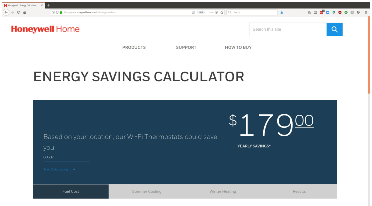

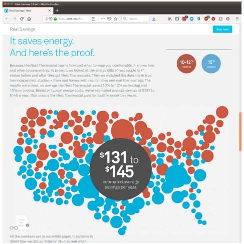

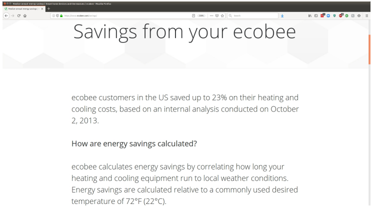

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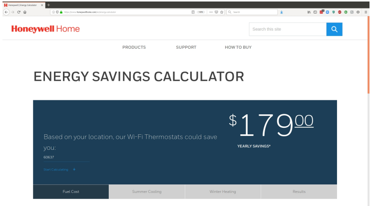

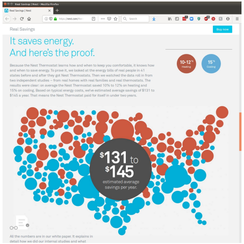

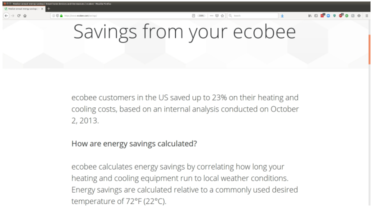

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    - Potential to have a big effect on private & social costs if widely adopted
- But claims based on engineering or correlation studies
    - "Your results may vary depending on your dynamic lifestyle."
- ⇒ True impact of smart thermostats on energy usage "in the field" is uncertain

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- Observed outcome: 18 months of high-frequency data on household energy use
    - Hourly electricity (~16 million observations)
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- Empirical model: difference-in-differences instrumental variables (DDIV)
    - Treatment status IVs for installation

Preview of Results

- Little evidence smart thermostats affect energy use
  - Overall effects neither statistically nor economically significant
  - Null effects robust to
    - Inclusion of numerous controls
    - Conditioning on various subsamples (e.g., by temperature, day of week, time of day)
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    - Exception: smart thermostats $\downarrow$ electricity use in high humidity
- Descriptive analysis of potential mechanisms
  - Use data on system events including user interactions with smart thermostat (~4 million observations)
  - Consistent with user behavior dampening energy savings
    - Users override setpoints (energy) inefficiently
    - High-efficiency types see savings

Contributions

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  - Subsidized by government...
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    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
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- Importance of basing decisions on field experiments, not engineering projections (Fowlie et al., 2018; Alpízar et al., 2019)
- Importance of publishing null effects for science (Tufano and List, 2019)
  - Burkhardt et al. (2019) relegate similar null effects of a Nest thermostat to a footnote

Overview

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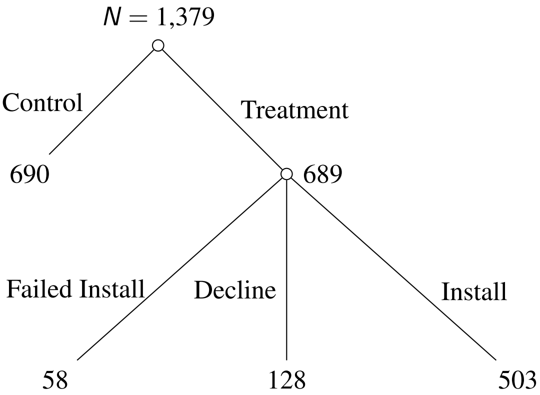
- Treatment: smart thermostat installed at no cost
- Outcomes recorded for 18 month period
  - July 2012 - December 2013

Subject Eligibility Summary

	Eligible	Not Eligible
Rent or own?	Own	Rent
Home Type	House or Condo	Apartment or Other
Phone	iPhone or Android	Blackberry or Other
# of Thermostats	1	≥ 2
A/C	Central Air	Box Unit, Fans, Other
Heating	Air Vents	Baseboard or Other
High-speed Internet?	Yes	No
Plan to move in next year?	No	Yes

Description of Randomization & Sample



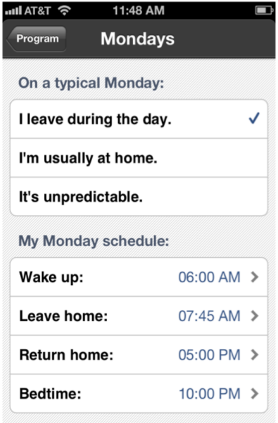
Treatment: Honeywell Z-Wave Touchscreen Smart Thermostat

Not Treatment: Honeywell Cadillac of Thermostats

Source: Reproduced without permission from List & Suskind (2019).

Treatment: Smart Thermostat Features

1. Programmable schedule



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   - Can toggle to more energy efficient setting when not home
   - Don't have to get off the couch when home

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3. Setpoint comparison analogous to Allcott (2011)

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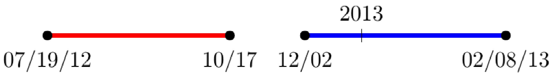
2. Website portal & smartphone app designed/hosted by Opower
3. Setpoint comparison analogous to Allcott (2011)
   - Descriptive norms with information on peer set point choices
   - Injunctive norms with efficiency ratings of set points

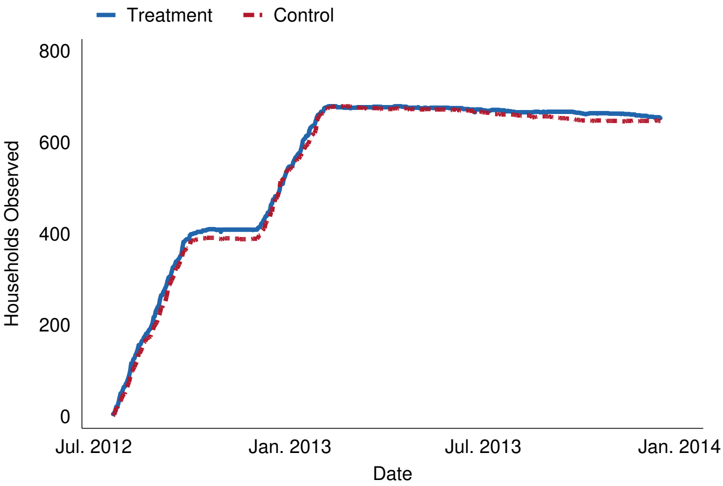
Timeline

Energy Use Data

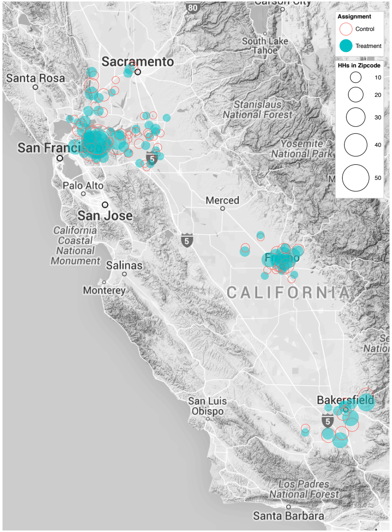
Assignment Date



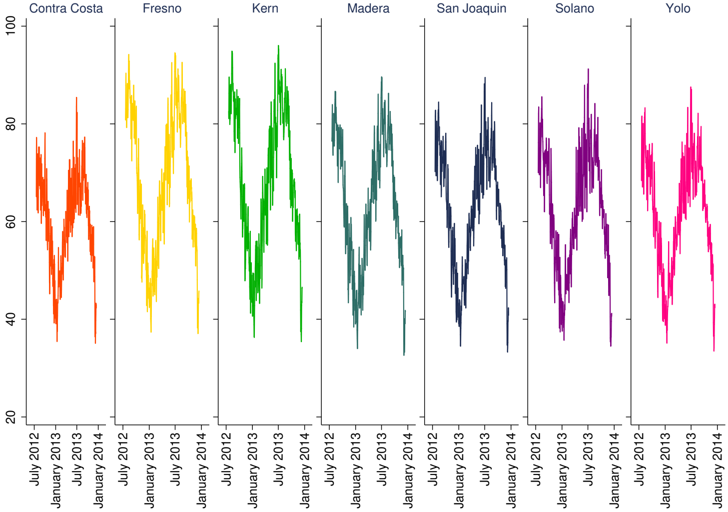
Experimental Data: Number of Households Observed by Date



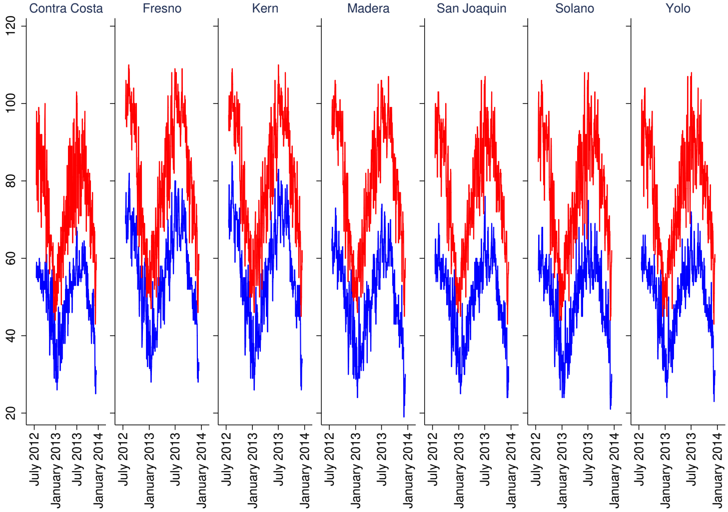
Spatial Balance



Mean Daily Temperature by County (°F)



Minimum & Maximum Daily Temperature by County (°F)



Daily Outdoor Temperature ($^{\circ}F$) Summary Statistics

Variable	Mean	Std. Dev.	Between Std. Dev.	Within Std. Dev.	Min.	Max.
Mean Daily Temp.	63.70	13.06	3.20	12.71	32.63	96.04
Minimum Daily Temp.	51.34	11.55	3.43	11.10	19.00	85.00
Maximum Daily Temp.	77.52	15.23	2.58	15.05	43.00	110.00
N			7			
$N \times T$			3,605			

Balance on Observables

Variable	All Waves $\mathbb{1}(Treated)$	Wave 1: N. CA $\mathbb{1}(Treated)$	Wave 2: C. CA $\mathbb{1}(Treated)$
Household Characteristics			
Family in the Household Indicator	0.026	-0.026	0.085
	(0.053)	(0.071)	(0.080)
Pets in the Household Indicator	0.015	0.020	0.008
	(0.029)	(0.038)	(0.045)
HER Subject Indicator	0.019	0.002	0.045
	(0.031)	(0.040)	(0.049)
Home Characteristics			
Pre-Period Energy Use			
N	1,385	821	564
R^2	0.013	0.019	0.021
F	0.731	0.822	0.687

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Multi-Family Home Indicator	-0.019	-0.024	0.039
	(0.080)	(0.091)	(0.166)
Year Home Built	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Size of Home (Sq. Ft.)	0.000	0.000	0.000
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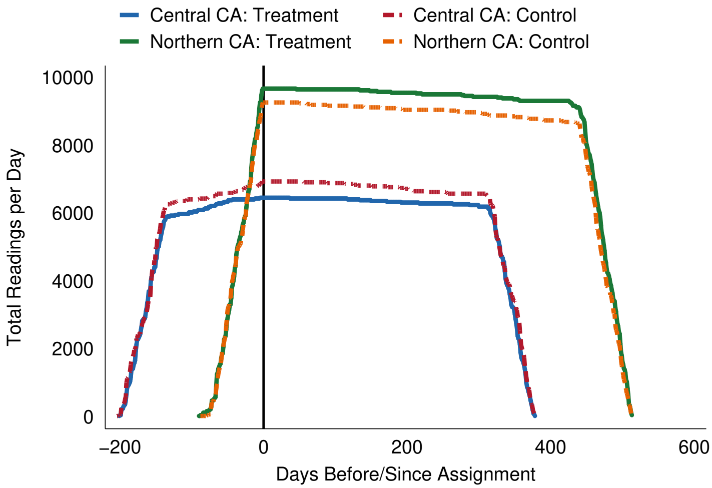
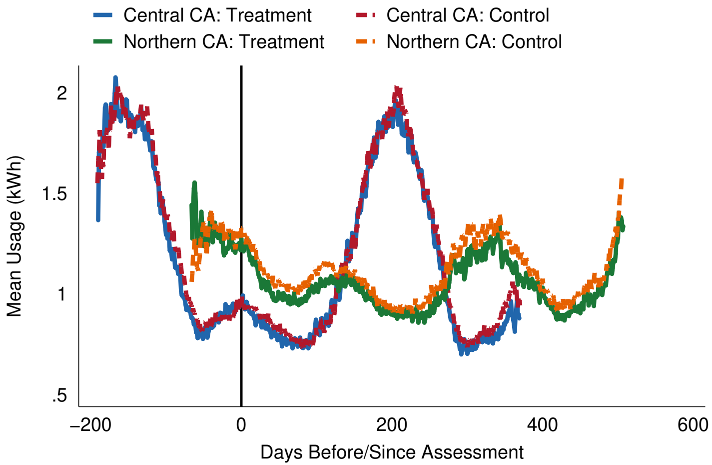
Experimental Data: Number of Readings by Experimental Status & Wave

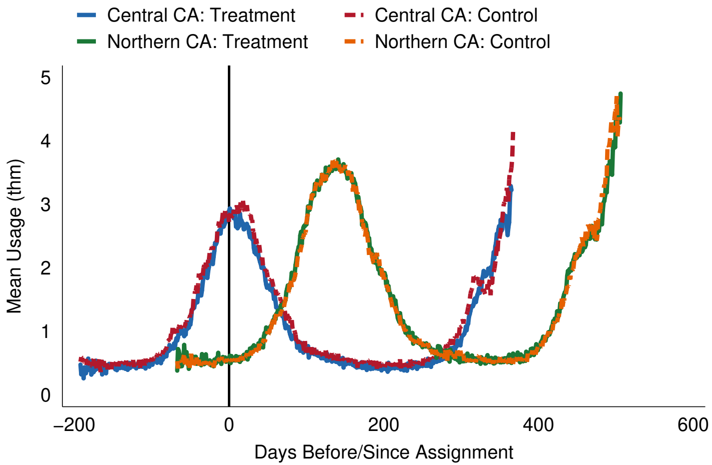


Average Electricity Use by Experimental Status & Wave



Only means based on 30 or more homes per day are included in the figure.

Average Natural Gas Use by Experimental Status & Wave



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- Estimate e_{it}^{j} separately for each j using two-stage least squares (2SLS) models

DDIV Model

- Second-stage equation

$$e_{it}^{j} = \alpha_i^j + \beta_t^j + \gamma^j S_i P_t + X_{it}\delta^j + u_{it}^j$$

  - S_i is an indicator for installation of a smart thermostat by household i
  - P_t is an indicator for post-assignment status in time period t
  - α_i^j is a household fixed effect
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  - X_{it} is a vector of controls
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  - Never observe control households on Opower platform
  - EIA Residential Energy Consumption Survey (RECS) 2-3 years after experiment:
    - Only 4.09% of all households in the survey and
    - Only 10.58% of observationally similar households own a smart thermostat

Interpretation of γ^j

- Under the assumptions of
  - Instrument exogeneity
  - One-sided noncompliance
    - Some households in treatment do not install a smart thermostat
    - But no households in control install a smart thermostat
- $\Rightarrow$ γ^j is the average treatment effect on the treated (ATT) (Cornelissen et al., 2016)
  - Average impact of a smart thermostat on the households that install one
- Is one-sided noncompliance a reasonable assumption? Untestable, but
  - Never observe control households on Opower platform
  - EIA Residential Energy Consumption Survey (RECS) 2-3 years after experiment:
    - Only 4.09% of all households in the survey and
    - Only 10.58% of observationally similar households own a smart thermostat
  - $\Rightarrow$ Suggestive evidence that bias unlikely to be large

Overview

- We estimate the effect of a smart thermostat on energy use multiple ways

1. Main (all waves)
    1. Electricity
    2. Natural gas

Overview

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   1. Electricity
   2. Natural gas
2. Heterogeneous treatment effects
   1. By ambient weather conditions
      1. Temperature bins
      2. Humidity quintiles
      3. Heat index quintiles
   2. By weekday/weekend & day of the week
   3. By hour of the day
   4. By hour of the day & weekday

Overview

- We estimate the effect of a smart thermostat on energy use multiple ways

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    2. Natural gas
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    3. By hour of the day
    4. By hour of the day & weekday
3. Threats to ID
    1. Time to installation: description
    2. Short pre-period: by wave (C. CA)

Electricity: Estimates of the Effect of a Smart Thermostat

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.031	-0.031	-0.003	-0.001	-0.001	0.026
	(0.036)	(0.035)	(0.022)	(0.022)	(0.022)	(0.017)
N	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734
rk Wald F	790.294	819.435	1,948.381	1,951.624	1,951.629	1,931.185
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day & Hour-of-Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: Estimates of the Effect of a Smart Thermostat

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.031	-0.031	-0.003	-0.001	-0.001	0.026
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HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day & Hour-of-Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

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Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day & Hour-of-Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: Estimates of the Effect of a Smart Thermostat

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (thm)					
$\hat{\gamma}^{thm}$	0.062	0.065	0.028	0.023	0.023	0.055**
	(0.060)	(0.049)	(0.028)	(0.026)	(0.026)	(0.022)
N	1,369	1,369	1,369	1,369	1,369	1,369
$N \times T$	677,304	677,304	677,304	677,304	677,304	677,304
rk Wald F	790.386	817.152	1,976.210	1,980.104	1,980.097	1,958.933
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Ambient Temperature Bins

	(1)	(2)	(3)	(4)	(5)
	$< 35\ ^\circ F$	$35 - 49\ ^\circ F$	$50 - 64\ ^\circ F$	$65 - 79\ ^\circ F$	$> 80\ ^\circ F$
	Power Use (kWh)				
$\hat{\gamma}^{kWh}$	-0.025	-0.035	-0.030*	-0.008	0.011
	(0.055)	(0.022)	(0.017)	(0.024)	(0.046)
N	1,372	1,376	1,379	1,379	1,378
$N \times T$	312,941	2,662,743	6,463,165	4,214,034	2,768,851
rk Wald F statistic	960.134	1,377.661	1,971.554	1,895.859	1,749.432
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: By Ambient Temperature Bins

	(1)	(2)	(3)	(4)	(5)
	$< 35\,°F$	$35 - 49\,°F$	$50 - 64\,°F$	$65 - 79\,°F$	$> 80\,°F$
			Power Use (thm)		
$\hat{\gamma}^{thm}$	-0.129	-0.046	0.008	0.002	0.034*
	(0.135)	(0.058)	(0.022)	(0.016)	(0.019)
N	1,360	1,364	1,369	1,365	619
$N \times T$	22,736	158,420	349,206	126,873	20,065
rk Wald F statistic	1,050.914	1,414.902	1,813.446	1,448.408	1,269.038
HH Fixed Effects	x	x	x	x	x
Month-of-Year Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Ambient Humidity Quintiles

	(1)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
			Power Use (kWh)		
$\hat{\gamma}^{kWh}$	0.050	-0.010	-0.021	-0.041**	-0.066***
	(0.048)	(0.024)	(0.019)	(0.018)	(0.020)
N	1,379	1,379	1,379	1,379	1,379
$N \times T$	3,313,684	3,333,963	3,255,920	3,239,969	3,278,198
rk Wald F	1,763.238	1,860.182	1,910.165	1,944.091	1,612.296
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Ambient Humidity Quintiles

	(1)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
			Power Use (kWh)		
$\hat{\gamma}^{kWh}$	0.050	-0.010	-0.021	-0.041**	-0.066***
	(0.048)	(0.024)	(0.019)	(0.018)	(0.020)
N	1,379	1,379	1,379	1,379	1,379
$N \times T$	3,313,684	3,333,963	3,255,920	3,239,969	3,278,198
rk Wald F	1,763.238	1,860.182	1,910.165	1,944.091	1,612.296
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: By Ambient Humidity Quintiles

	(1)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
			Power Use (thm)		
$\hat{\gamma}^{thm}$	0.004	-0.010	-0.005	0.047	-0.022
	(0.017)	(0.025)	(0.036)	(0.044)	(0.067)
N	1,367	1,369	1,369	1,369	1,367
$N \times T$	141,016	133,650	132,648	153,013	116,975
rk Wald F	1,356.189	1,740.682	1,908.480	1,522.235	1,306.659
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Ambient Heat Index Quintiles

	(1) Quintile 1	(2) Quintile 2	(3) Quintile 3	(4) Quintile 4	(5) Quintile 5
	Power Use (kWh)				
$\hat{\gamma}^{kWh}$	-0.036	-0.030	-0.026	-0.009	0.009
	(0.022)	(0.019)	(0.019)	(0.024)	(0.043)
N	1,376	1,379	1,379	1,379	1,378
$N \times T$	3,296,464	3,272,861	3,296,156	3,273,130	3,283,123
rk Wald F	1,381.488	1,927.034	1,955.091	1,883.345	1,770.575
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: By Ambient Heat Index Quintiles

	(1)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
			Power Use (thm)		
$\hat{\gamma}^{thm}$	-0.060	-0.004	-0.004	-0.003	0.009
	(0.066)	(0.044)	(0.024)	(0.018)	(0.015)
N	1,364	1,366	1,369	1,367	1,365
$N \times T$	135,502	136,401	134,876	135,317	135,204
rk Wald F	1,364.503	1,468.623	1,403.564	1,797.169	1,406.956
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity & Natural Gas: By Weekday/Weekend

	(1)	(2)	(3)	(4)
	Weekday	Weekend	Weekday	Weekend
	Power Use (kWh)		Power Use (thm)	
$\hat{\gamma}^j$	-0.002	0.002	0.022	0.028
	(0.022)	(0.023)	(0.026)	(0.027)
N	1,379	1,379	1,369	1,369
$N \times T$	11,720,215	4,701,519	484,958	192,346
rk Wald F	1,951.954	1,950.200	1,978.155	1,983.795
Weather Controls	x	x	x	x
HH Fixed Effects	x	x	x	x
MOY Effects	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Day of the Week

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
	Power Use (kWh)						
$\hat{\gamma}^{kWh}$	-0.014	-0.007	-0.001	0.005	0.005	0.010	-0.006
	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
N	1,379	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	2,331,710	2,331,777	2,331,619	2,362,409	2,362,700	2,362,920	2,338,599
rk Wald F	1,941.134	1,936.473	1,933.095	1,972.928	1,966.289	1,952.711	1,946.894
Weather Controls	x	x	x	x	x	x	x
HH Fixed Effects	x	x	x	x	x	x	x
MOY Effects	x	x	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: By Day of the Week

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
	Power Use (thm)						
$\hat{\gamma}^{thm}$	0.015	0.026	0.024	0.018	0.017	0.033	0.024
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.031)	(0.029)
N	1,369	1,369	1,369	1,369	1,369	1,369	1,369
$N \times T$	96,480	96,480	96,474	97,760	97,764	97,771	94,575
rk Wald F	1,965.987	1,959.102	1,960.855	1,998.501	1,993.533	1,984.444	1,981.320
Weather Controls	x	x	x	x	x	x	x
HH Fixed Effects	x	x	x	x	x	x	x
MOY Effects	x	x	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Hour of the Day

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	12:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00
	Power Use (kWh)											
$\hat{\gamma}^{kWh}$ (AM)	-0.022	-0.012	-0.020	-0.030	-0.015	0.009	0.003	-0.003	0.005	-0.029	-0.041	-0.042
	(0.027)	(0.023)	(0.021)	(0.021)	(0.021)	(0.023)	(0.024)	(0.027)	(0.030)	(0.036)	(0.039)	(0.042)
$\hat{\gamma}^{kWh}$ (PM)	-0.028	-0.005	0.015	0.021	0.046	0.076*	0.048	0.035	-0.004	-0.032	-0.022	-0.019
	(0.045)	(0.047)	(0.048)	(0.047)	(0.045)	(0.042)	(0.039)	(0.036)	(0.034)	(0.032)	(0.031)	(0.027)
N	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	~684K	~684K	~684K	~684K	~684K	~684K	~684K	~684K	~684K	~684K	~684K	~684K

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.
All models include weather controls, HH fixed effects, MOY effects, and DOW effects. Min(rk Wald F statistic)=1,946.106.

Electricity: By Hour of the Day on Weekdays Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	12:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00
							Power Use (kWh)					
$\hat{\gamma}^{kWh}$ (AM)	-0.026	-0.015	-0.025	-0.036*	-0.017	0.011	0.000	-0.010	0.003	-0.032	-0.039	-0.042
	(0.028)	(0.024)	(0.022)	(0.021)	(0.021)	(0.023)	(0.025)	(0.027)	(0.030)	(0.036)	(0.040)	(0.042)
$\hat{\gamma}^{kWh}$ (PM)	-0.027	-0.009	0.010	0.016	0.051	0.085*	0.053	0.036	-0.007	-0.035	-0.022	-0.027
	(0.045)	(0.048)	(0.049)	(0.050)	(0.047)	(0.044)	(0.041)	(0.038)	(0.035)	(0.033)	(0.032)	(0.028)
N	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	~488K	~488K	~488K	~488K	~488K	~488K	~488K	~488K	~488K	~488K	~488K	~488K

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects. Min(rk Wald F statistic)=1,946.422.

Threats to ID

- Treated may not install a smart thermostat quickly (slow-compliance)

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  - Time to installation is short

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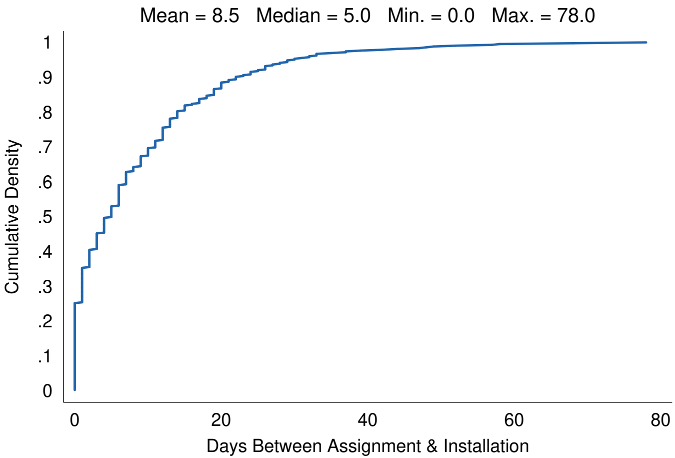
- No pre-period observations for some N. CA households

Threats to ID

- Treated may not install a smart thermostat quickly (slow-compliance)
  - Time to installation is short
- No pre-period observations for some N. CA households
  - Conditioning on C. CA wave yields similar results

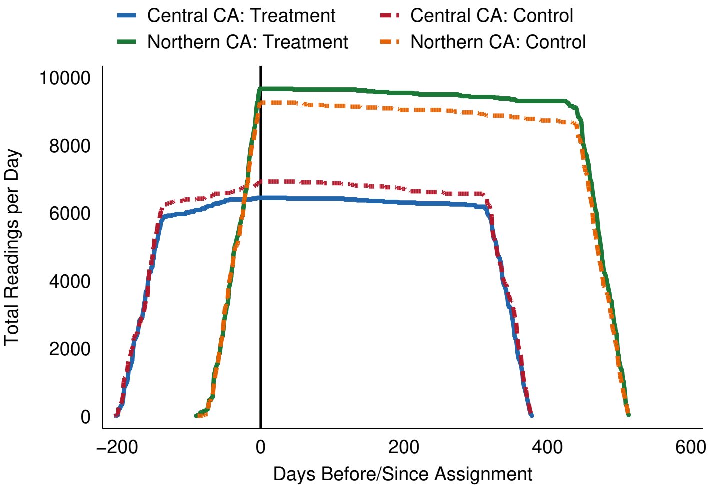
Distribution of Time to Installation



Cumulative density conditional on eventual installation.

▸ Unconditional Distribution

Total Electricity Readings by Experimental Status & Wave



Electricity: Estimates of the Effect of a Smart Thermostat (C. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	0.009	0.006	0.002	0.002	0.002	-0.001
	(0.029)	(0.028)	(0.025)	(0.025)	(0.025)	(0.023)
N	564	564	564	564	564	564
$N \times T$	6,691,885	6,691,885	6,691,885	6,691,885	6,691,885	6,691,885
rk Wald F	677.494	677.449	1,352.535	1,352.620	1,352.619	1,365.852
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day & Hour-of-Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: Estimates of the Effect of a Smart Thermostat (C. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (thm)					
$\hat{\gamma}^{thm}$	-0.003	0.007	0.001	0.001	0.001	-0.021
	(0.044)	(0.031)	(0.027)	(0.026)	(0.026)	(0.026)
N	564	564	564	564	564	564
$N \times T$	279,061	279,061	279,061	279,061	279,061	279,061
rk Wald F	675.636	675.284	1,376.620	1,376.557	1,376.527	1,388.599
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day Effects						x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Overview

- Provide descriptive evidence about possible explanations for our null result
  - Data on user interactions with smart thermostat
  - Descriptive evidence because we only observe if smart thermostat installed

Overview

- Provide descriptive evidence about possible explanations for our null result
  - Data on user interactions with smart thermostat
  - Descriptive evidence because we only observe if smart thermostat installed

1. HVAC events data description

Overview

- Provide descriptive evidence about possible explanations for our null result
  - Data on user interactions with smart thermostat
  - Descriptive evidence because we only observe if smart thermostat installed

1. HVAC events data description
2. Potential mechanisms
   1. Do users program their smart thermostats?
   2. Do users program their smart thermostats for energy savings?
   3. Do users deviate from their programed schedules?
   4. Do user deviations increase or decrease energy use?
   5. Do smart thermostats save any users energy?

Events Data Description

- Observe: exact time of HVAC events
  - Ambient temperature
  - Temperature settings
  - HVAC state (heating, cooling, fan)

Events Data Description

- Observe: exact time of HVAC events
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  - Temperature settings
  - HVAC state (heating, cooling, fan)
- Do not observe: type of temperature setting
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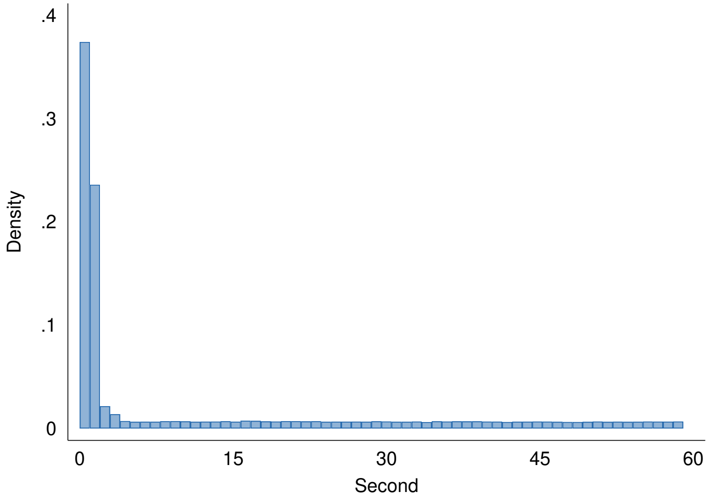
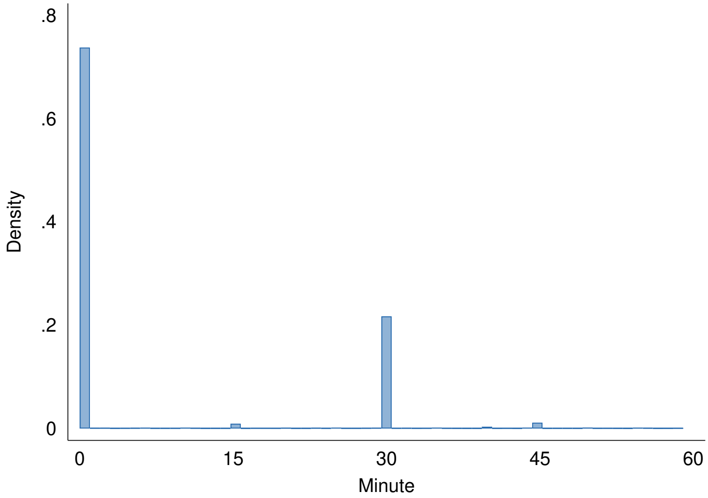
- Do not observe: events data for all installer households/time periods

Density of Temperature Changes by Second of the Minute



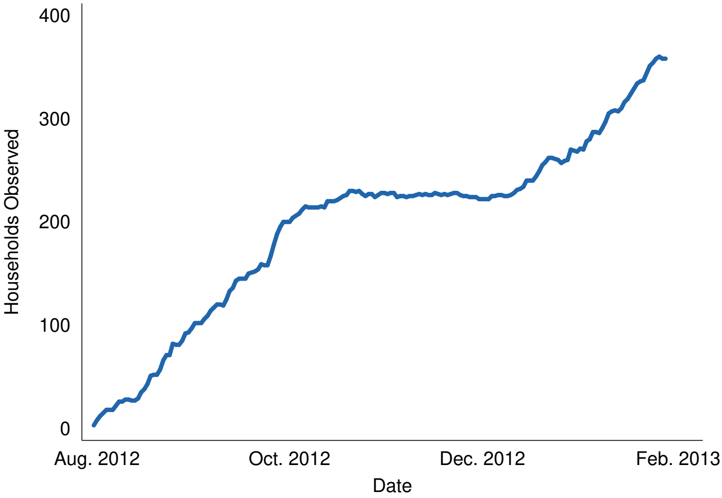
Density of Permanent Setpoints by Minute of the Hour



User Interactions Summary Statistics by Wave

	Northern California			Central California			All		
Variables	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Ambient Temp.	69.07	5.20	314,428	66.88	4.38	25,240	68.91	5.17	339,668
Cooling Setpoints	78.84	4.10	52,861	78.20	4.55	2,975	78.80	4.12	55,836
Heating Setpoints	63.89	5.58	71,667	64.65	5.45	5,749	63.95	5.58	77,416
Cooling Overrides	77.49	3.88	14,082	77.55	5.01	1,191	77.50	3.98	15,273
Heating Overrides	67.36	4.15	40,983	68.17	4.59	6,490	67.47	4.22	47,473
N		233			133			365	
$N \times T$		350,175			28,365			378,540	

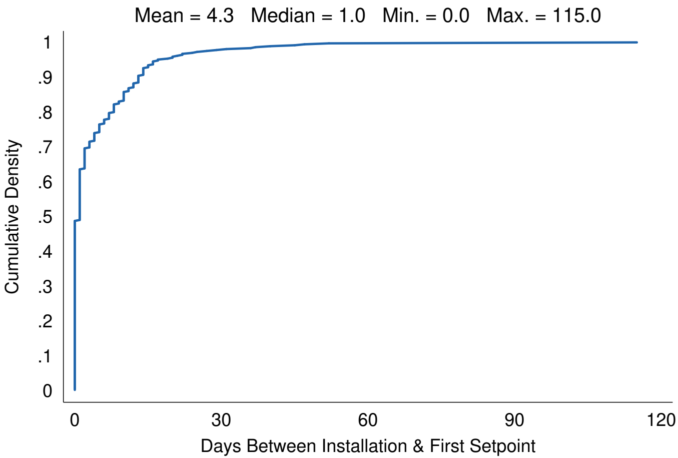
Events Data: Number of Households Observed by Date



Outline

1. HVAC events data description ✓
2. Potential mechanisms
    1. Do users program their smart thermostats?
    2. Do users program their smart thermostats for energy savings?
    3. Do users deviate from their programed schedules?
    4. Do user deviations increase or decrease energy use?
    5. Do smart thermostats save any users energy?

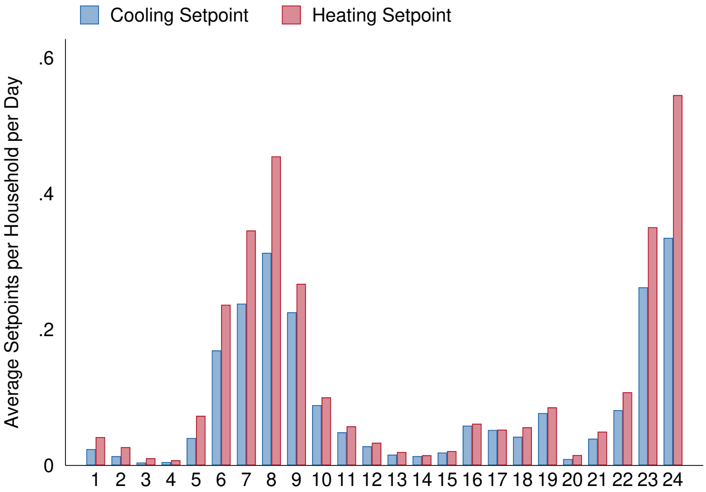
Distribution of Time from Installation to First Permanent Setpoint



Cumulative density conditional on observing the household in the HVAC events data.

Breakdown

Average Permanent Setpoints per Household per Day by Hour



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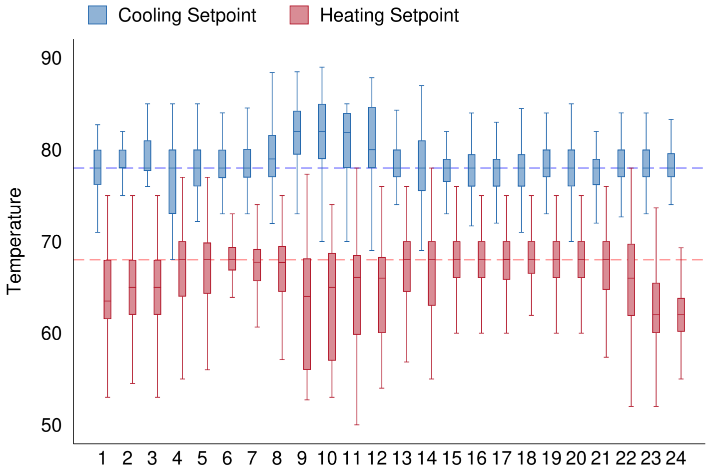
Box & Whisker Plots of Permanent Setpoints by Hour



Dashed lines represent EPA recommended cooling/heating settings.

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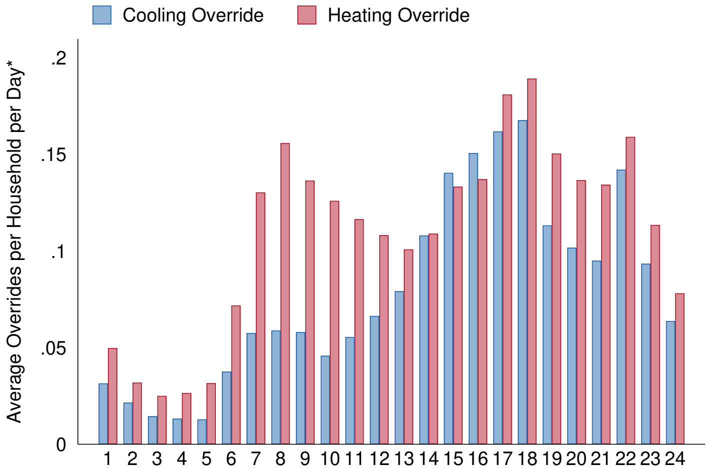
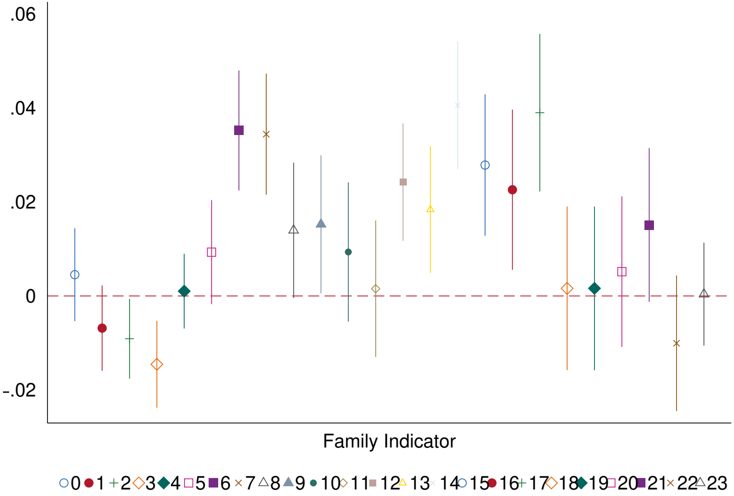
Average Temporary Overrides per Household per Day by Hour



* Cooling/heating days defined as those when the HVAC system cooled/heated the home.

Effect of Family in Household on Pr(Temporary Override) by Hour



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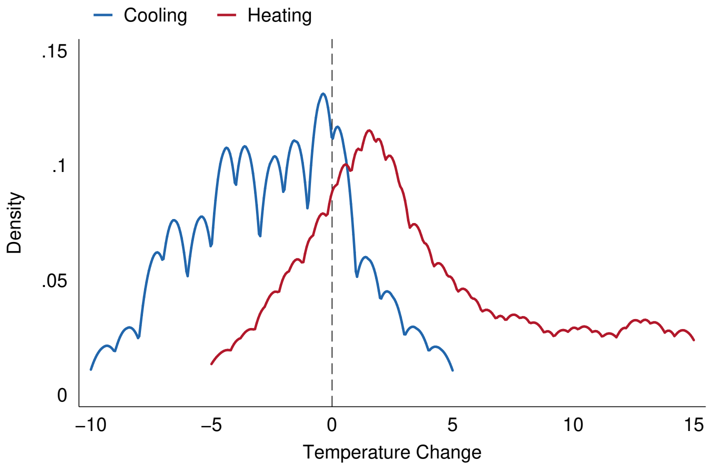
Density of Override & Setpoint Temperature Differences by HVAC State



Densities truncated at the 5th and 95th percentiles.

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   4. Do user deviations increase or decrease energy use? $\uparrow e^j$
   5. Do smart thermostats save any users energy?

Estimation of Effects by Energy-Efficiency Type

- Engineering estimates: smart thermostats reduce energy use absent human intervention
    - High-efficiency type: robots in engineer models
    - Low–efficiency type: people in economist models

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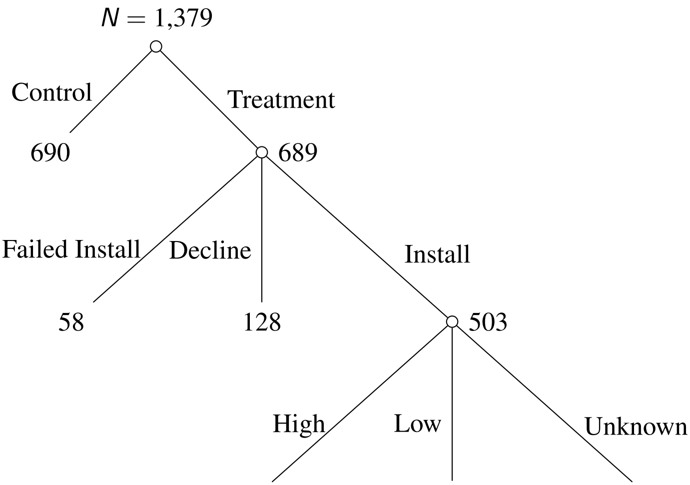
Estimation of Effects by Energy-Efficiency Type

- Engineering estimates: smart thermostats reduce energy use absent human intervention
  - High-efficiency type: robots in engineer models
  - Low–efficiency type: people in economist models
- Use events data to classify households by energy-efficiency type
- Estimate separate effects by type
  - Are engineering estimates just wrong?
  - Or wrong because engineers don't account for user behavior?

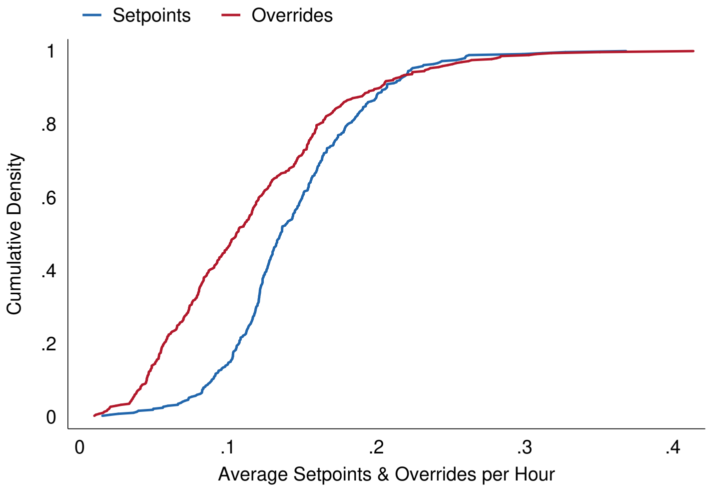
Description of Randomization & Sample



Classification by Energy-Efficiency Type

- High-efficiency type
  - Many setpoints/few overrides
- Low–efficiency type
  - Few setpoints/many overrides
- Unknown type
  - Those we don't observe events data for

Distributions of Setpoints & Overrides



Model Overview

- Difference-in-differences intention-to-treat (DDITT) model

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- Estimate e^j_{it} separately for each j using panel data models

DDITT Model

- Estimating equation

$$e^j_{it} = \alpha^j_i + \beta^j_t + \gamma^j_H T_i R^{High}_i P_t + \gamma^j_L T_i R^{Low}_i P_t + \gamma^j_? T_i R^?_i P_t + X_{it}\beta^j_X + u^j_{it}$$

  - T_i is an indicator for household i's treatment status in our experiment
  - R^k_i is an indicator for household i being of energy-efficiency type k
  - P_t is an indicator for post-assignment status in time period t
  - α^j_i is a household fixed effect
  - β^j_t is a time effect
  - X_{it} is a vector of controls
  - u^j_{it} is a household/time varying unobservable
- γ^j_k is the ITT effect of a smart thermostat on energy j for households of type k

ITT Model

- Estimating equation

$$e_{it}^{j} = \alpha_i^j + \beta_t^j + \gamma_H^j T_i R_i^{High} P_t + \gamma_L^j T_i R_i^{Low} P_t + \gamma_?^j T_i R_i^? P_t + X_{it}\beta_X^j + u_{it}^j$$

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Natural Gas: Estimates by Setpoint-Efficiency Type (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
				Percentile		
	Baseline	10	25	50	75	90
				Power Use (thm)		
$\hat{\gamma}^{thm}$	0.047					
	(0.037)					
$\hat{\gamma}^{thm}_{High}$		-0.070*	-0.104**	-0.138***	-0.173***	-0.291***
		(0.042)	(0.043)	(0.046)	(0.057)	(0.073)
$\hat{\gamma}^{thm}_{Low}$		-0.049	0.104	0.018	-0.018	-0.041
		(0.143)	(0.100)	(0.065)	(0.051)	(0.044)
N	805	805	805	805	805	805
$N \times T$	398,243	398,243	398,243	398,243	398,243	398,243

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, day effects, and hour-of-day effects.

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Natural Gas: Estimates by Override-Efficiency Type (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
				Percentile		
	Baseline	10	25	50	75	90
				Power Use (thm)		
$\hat{\gamma}^{thm}$	0.047					
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$\hat{\gamma}^{thm}_{Low}$		-0.085**	-0.072	-0.078	-0.032	0.423***
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All models include weather controls, HH fixed effects, day effects, and hour-of-day effects.

Summary

- Evidence that users do use the features of their smart thermostats
  - Program their thermostats well
  - Deviate from their programed schedules
- High-efficiency type users see savings
  - Results are not robust across all waves/energy types
  - But are most significant/sensible for samples closest to the events data

Conclusions

- We estimate the causal effect of smart thermostats on energy use
  - Based on a field experiment
  - And high-frequency energy use data
- Robust evidence of a null effect
- Descriptive evidence consistent with user behavior dampening savings
  - Users override setpoints (energy) inefficiently
  - High-efficiency types see savings
- Decisions should be based on evidence that accounts for human behavior!!!

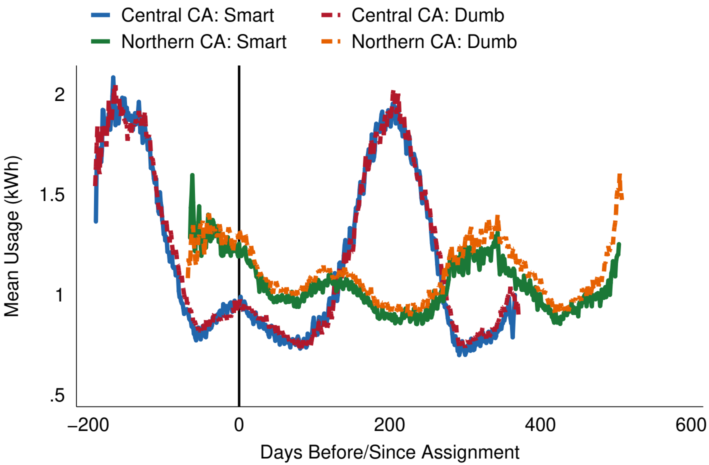
Thank You

Comments and suggestions are welcomed!

: cclapp@uchicago.edu
: www.chrisclapp.org
: @ChrisMClapp

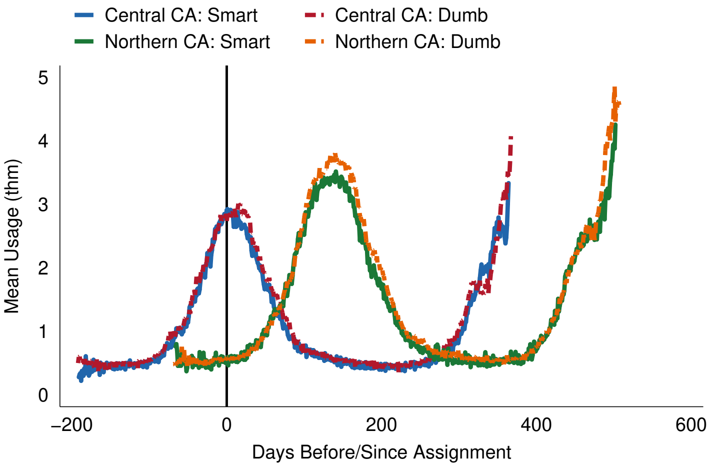
ABC

Average Electricity Usage by Thermostat Type & Experimental Wave



Only means based on 30 or more homes per day are included in the figure.

Average Natural Gas Usage by Thermostat Type & Experimental Wave



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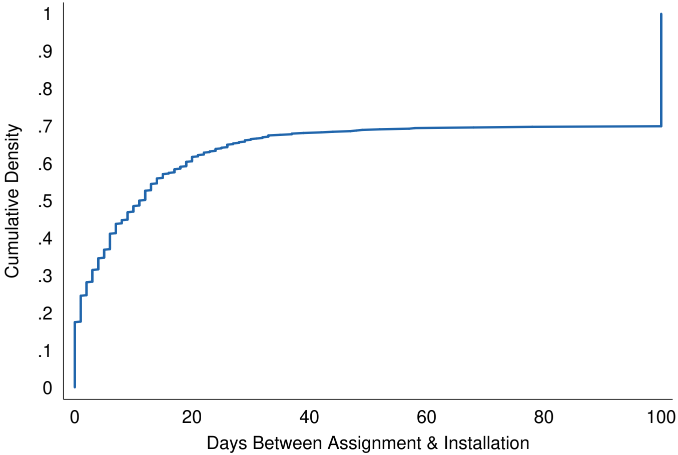
Unconditional Distribution of Time to Installation



Never−installers topcoded at 100 days.

Return

Alternative DDIV Model

- Second-stage equation

$$e_{it}^j = \alpha_i^j + \beta_t^j + \gamma^j S_{it} + X_{it}\delta^j + u_{it}^j$$

  - S_{it} is an indicator equal to one if household i has a smart thermostat installed in period t
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- Two-stage least squares (2SLS) estimation with

$$E\left[Z_{it}^j u_{it}^j\right] = 0$$

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Return

Electricity: By Ambient Temperature Quintiles

	(1)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
	Power Use (kWh)				
$\hat{\gamma}^{kWh}$	-0.036	-0.033*	-0.024	-0.008	0.009
	(0.022)	(0.019)	(0.019)	(0.024)	(0.044)
N	1,376	1,379	1,379	1,379	1,378
$N \times T$	3,345,085	3,541,064	3,239,489	3,102,224	3,193,872
rk Wald F	1,379.806	1,920.331	1,966.682	1,879.175	1,769.185
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: By Ambient Temperature Quintiles

	(1) Quintile 1	(2) Quintile 2	(3) Quintile 3	(4) Quintile 4	(5) Quintile 5
			Power Use (thm)		
$\hat{\gamma}^{thm}$	-0.054	-0.013	0.005	-0.008	0.010
	(0.064)	(0.038)	(0.023)	(0.018)	(0.015)
N	1,364	1,366	1,369	1,368	1,365
$N \times T$	145,525	147,440	120,087	138,512	125,737
rk Wald F	1,375.353	1,587.271	1,323.568	1,802.507	1,377.126
HH Fixed Effects	x	x	x	x	x
MOY Effects	x	x	x	x	x
Day-of-Week Effects	x	x	x	x	x

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Electricity: By Hour of the Day on Weekends Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	12:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00
	Power Use (kWh)											
$\hat{\gamma}^{kWh}$ (AM)	-0.010	-0.006	-0.007	-0.017	-0.009	0.004	0.011	0.013	0.011	-0.022	-0.047	-0.041
	(0.028)	(0.024)	(0.022)	(0.022)	(0.021)	(0.023)	(0.024)	(0.027)	(0.032)	(0.038)	(0.042)	(0.044)
$\hat{\gamma}^{kWh}$ (PM)	-0.032	0.005	0.027	0.031	0.034	0.053	0.037	0.032	0.002	-0.026	-0.023	0.000
	(0.048)	(0.050)	(0.050)	(0.048)	(0.045)	(0.043)	(0.040)	(0.037)	(0.036)	(0.034)	(0.031)	(0.029)
N	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	~196K	~196K	~196K	~196K	~196K	~196K	~196K	~196K	~196K	~196K	~196K	~196K

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.
All models include weather controls, HH fixed effects, MOY effects, and DOW effects. Min(rk Wald F statistic)=1,942.447.

Electricity: Estimates of the Effect of a Smart Thermostat (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.055	-0.061	-0.016	-0.016	-0.016	-0.003
	(0.058)	(0.058)	(0.046)	(0.046)	(0.046)	(0.041)
N	815	815	815	815	815	815
$N \times T$	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849
rk Wald F	379.956	380.003	670.871	670.765	670.766	639.637
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day & Hour-of-Day Effects						x

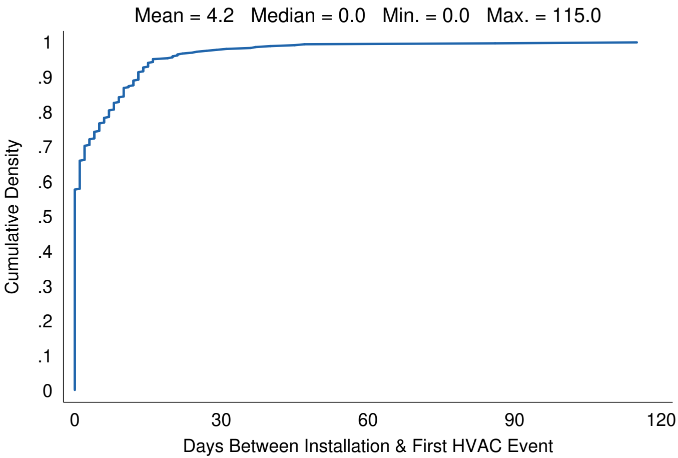
Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Natural Gas: Estimates of the Effect of a Smart Thermostat (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
			Power Use (thm)			
$\hat{\gamma}^{thm}$	-0.009	0.009	0.085	0.075	0.075	0.069
	(0.061)	(0.063)	(0.068)	(0.066)	(0.066)	(0.055)
N	805	805	805	805	805	805
$N \times T$	398,243	398,243	398,243	398,243	398,243	398,243
rk Wald F	377.042	377.090	672.580	672.617	672.609	641.179
Weather Controls		x	x	x	x	x
HH Fixed Effects			x	x	x	x
Month-of-Year Effects				x	x	
Day-of-Week Effects					x	
Day Effects						x

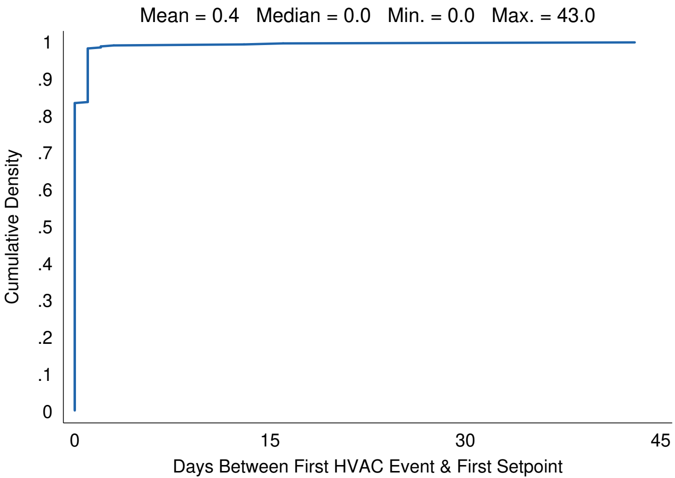
Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Distribution of Time from Installation to First HVAC Event



Cumulative density conditional on observing the household in the HVAC events data.

Distribution of Time from First HVAC Event to First Permanent Setpoint



Return

ABC

Natural Gas: Estimates by Setpoint-Efficiency Type (All Waves)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	10	30	50	70	90
	Power Use (thm)					
$\hat{\gamma}^{kWh}$	0.018					
	(0.020)					
$\hat{\gamma}^{kWh}_{High}$		-0.026	-0.075***	-0.079***	-0.098***	-0.141**
		(0.024)	(0.025)	(0.027)	(0.037)	(0.067)
$\hat{\gamma}^{kWh}_{Low}$		-0.035	0.058*	0.015	-0.004	-0.019
		(0.047)	(0.034)	(0.030)	(0.025)	(0.023)
N	1,369	1,369	1,369	1,369	1,369	1,369
$N \times T$	677,304	677,304	677,304	677,304	677,304	677,304

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Natural Gas: Estimates by Override-Efficiency Type (All Waves)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	10	30	50	70	90
	Power Use (thm)					
$\hat{\gamma}^{thm}$	0.018					
	(0.020)					
$\hat{\gamma}^{thm}_{High}$		0.046	-0.011	-0.007	-0.023	-0.035
		(0.104)	(0.047)	(0.037)	(0.029)	(0.024)
$\hat{\gamma}^{thm}_{Low}$		-0.032	-0.032	-0.039	-0.033	0.013
		(0.023)	(0.024)	(0.024)	(0.028)	(0.047)
N	1,369	1,369	1,369	1,369	1,369	1,369
$N \times T$	677,304	677,304	677,304	677,304	677,304	677,304

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Electricity: Estimates by Setpoint-Efficiency Type (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	10	30	50	70	90
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.011					
	(0.031)					
$\hat{\gamma}^{kWh}_{High}$		-0.033	-0.045	0.019	0.050	0.091
		(0.040)	(0.044)	(0.034)	(0.037)	(0.066)
$\hat{\gamma}^{kWh}_{Low}$		0.099	0.042	-0.082	-0.072	-0.040
		(0.070)	(0.063)	(0.070)	(0.054)	(0.041)
N	815	815	815	815	815	815
$N \times T$	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Electricity: Estimates by Override-Efficiency Type (N. CA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	10	30	50	70	90
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.011					
	(0.031)					
$\hat{\gamma}^{kWh}_{High}$		-0.037	-0.064	-0.011	-0.010	-0.024
		(0.121)	(0.051)	(0.039)	(0.033)	(0.039)
$\hat{\gamma}^{kWh}_{Low}$		-0.025	-0.007	-0.046	-0.089	-0.079
		(0.040)	(0.049)	(0.068)	(0.128)	(0.108)
N	815	815	815	815	815	815
$N \times T$	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849	9,729,849

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Electricity: Estimates by Setpoint-Efficiency Type (All Waves)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	10	30	50	70	90
	Power Use (kWh)					
$\hat{\gamma}^{kWh}$	-0.001					
	(0.017)					
$\hat{\gamma}^{kWh}_{High}$		-0.021	-0.006	0.019	0.050**	0.108***
		(0.023)	(0.024)	(0.021)	(0.025)	(0.042)
$\hat{\gamma}^{kWh}_{Low}$		0.029	-0.028	-0.041	-0.034	-0.023
		(0.038)	(0.037)	(0.032)	(0.026)	(0.022)
N	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Electricity: Estimates by Override-Efficiency Type (All Waves)

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	20	30	50	70	90
				Power Use (thm)		
$\hat{\gamma}^{kWh}$	-0.001					
	(0.017)					
$\hat{\gamma}^{kWh}_{High}$		-0.009	-0.043	-0.001	0.001	-0.002
		(0.044)	(0.035)	(0.027)	(0.024)	(0.022)
$\hat{\gamma}^{kWh}_{Low}$		-0.015	-0.006	-0.022	-0.036	-0.073
		(0.023)	(0.024)	(0.028)	(0.035)	(0.051)
N	1,379	1,379	1,379	1,379	1,379	1,379
$N \times T$	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734	16,421,734

Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

All models include weather controls, HH fixed effects, MOY effects, and DOW effects.

Return

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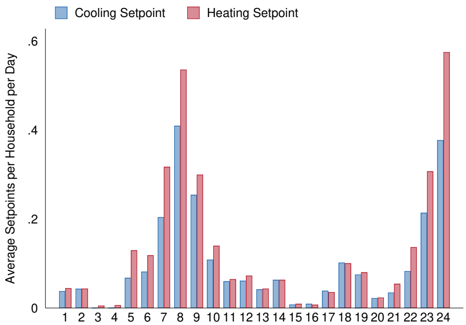
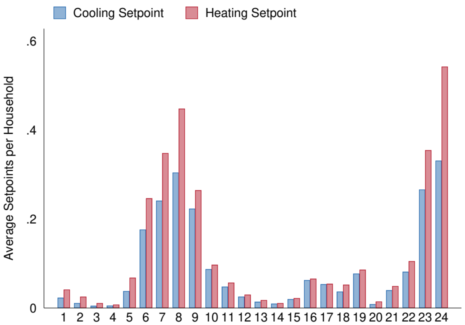
Do Families Program Fewer Setpoints?

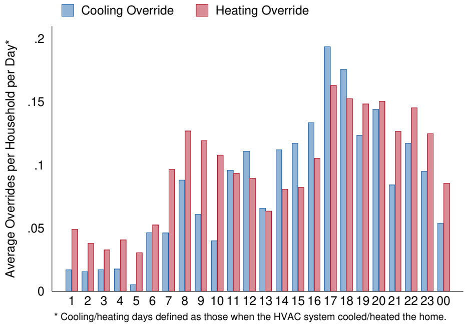


Individual Households

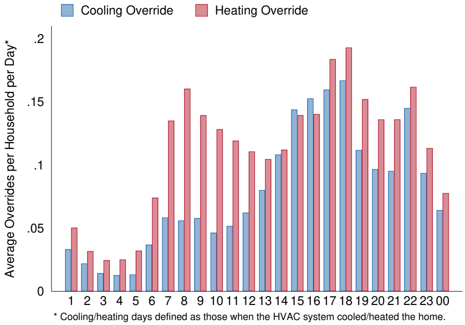


Family Households

Do Families Deviate from Programed Schedules More Often?

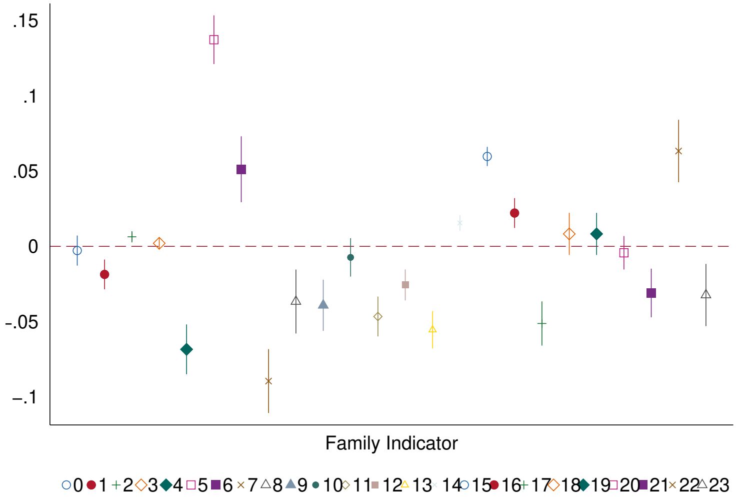


Individual Households



Family Households

Do Families Program More Setpoints?



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