Do Smart Technologies Deliver?
Smart Thermostats and Energy Conservation

Alec Brandon[1]
Christopher M. Clapp[1]
John A. List[1]
Robert Metcalfe[2]
Michael Price[3]

[1] University of Chicago
[2] Boston University
[3] University of Alabama

March 10, 2020

Smart Thermostats Month at EPIC!

	Casey	Chris
		
Thermostat	ecobee	Honeywell
Where	Canada	California
Treatment	Smart-eco+	Smart
Control	Smart-No eco+	Traditional
Effects	TOU Shift	Null

Background

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

Background

- Private costs
  - Average US household uses 166.3 million BTU of energy / year (EIA, 2019a)
  - ~$2,200 in energy bills / year (EIA, 2018)
- Social costs
  - Residential energy use produces 1 billion metric tons of CO_2 / year (EIA, 2019b)
  - ~20% of all US carbon pollution

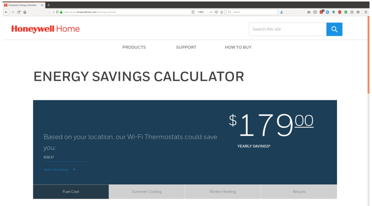
Technological Innovation

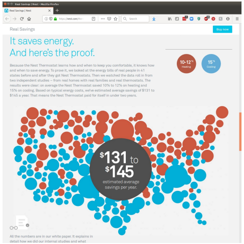
- Largest share of residential energy (~40%) goes to heating & cooling (EIA, 2019a)

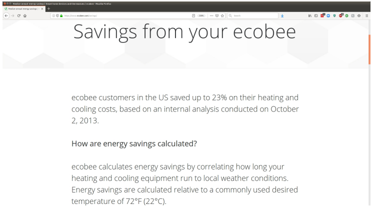
Technological Innovation

- Largest share of residential energy (~40%) goes to heating & cooling (EIA, 2019a)
- $\Rightarrow$ Traditional $\rightarrow$ smart thermostat

Big Savings!?!

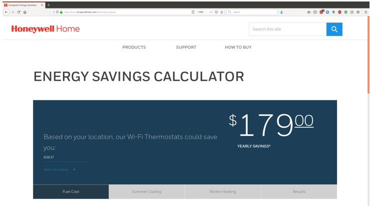


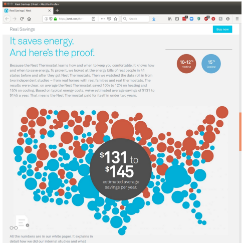


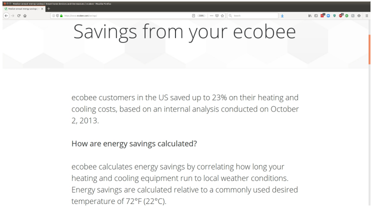


- Smart thermostat claim: $\uparrow$ efficiency $\Rightarrow$ $\downarrow$ energy use w/out $\downarrow$ consumer utility
  - Potential to have a big effect on private & social costs if widely adopted

Big Savings!?!

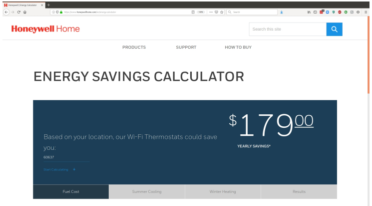


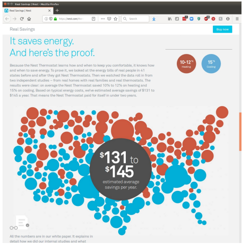


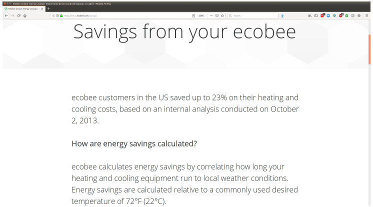


- Smart thermostat claim: $\uparrow$ efficiency $\Rightarrow$ $\downarrow$ energy use w/out $\downarrow$ consumer utility
  - Potential to have a big effect on private & social costs if widely adopted
- But claims based on engineering or correlation studies

Big Savings!?!

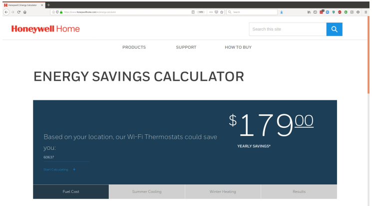


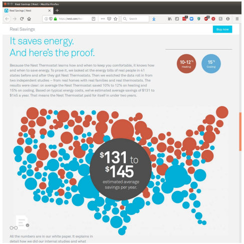


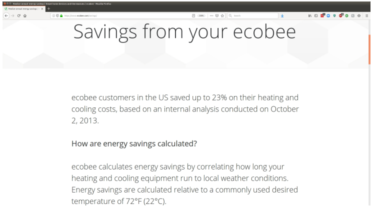


- Smart thermostat claim: $\uparrow$ efficiency $\Rightarrow$ $\downarrow$ energy use w/out $\downarrow$ consumer utility
  - Potential to have a big effect on private & social costs if widely adopted
- But claims based on engineering or correlation studies
  - "Your results may vary depending on your dynamic lifestyle."

Big Savings!?!







- Smart thermostat claim: $\uparrow$ efficiency $\Rightarrow$ $\downarrow$ energy use w/out $\downarrow$ consumer utility
  - 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."
- $\Rightarrow$ True impact of smart thermostats on energy usage "in the field" is uncertain

Research Agenda

- Goal: Test the hypothesis that smart thermostats reduce energy consumption

Research Agenda

- Goal: Test the hypothesis that smart thermostats reduce energy consumption
- Data: field experiment conducted by Opower & Honeywell w/ Pacific Gas & Electric (PG&E)
  - Treatment: free installation of Honeywell smart thermostat linked to Opower platform

Research Agenda

- Goal: Test the hypothesis that smart thermostats reduce energy consumption
- Data: field experiment conducted by Opower & Honeywell w/ Pacific Gas & Electric (PG&E)
    - Treatment: free installation of Honeywell smart thermostat linked to Opower platform
- Observed outcome: 18 months of high-frequency data on household energy use
    - Hourly electricity (~16 million observations)
    - Daily natural gas (~700 thousand observations)

Research Agenda

- Goal: Test the hypothesis that smart thermostats reduce energy consumption
- Data: field experiment conducted by Opower & Honeywell w/ Pacific Gas & Electric (PG&E)
  - Treatment: free installation of Honeywell smart thermostat linked to Opower platform
- Observed outcome: 18 months of high-frequency data on household energy use
  - Hourly electricity (~16 million observations)
  - Daily natural gas (~700 thousand observations)
- 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)
    - Exception: smart thermostats $\downarrow$ electricity use in high humidity

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)
    - 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

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies

Contributions

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies
  - ... and utilities
    - EPA/DOE ENERGY STAR partners with 17 utility companies who sponsor rebates
    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
    - 100% of residents in Nevada can receive a smart thermostat for free

Contributions

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies
  - ... and utilities
    - EPA/DOE ENERGY STAR partners with 17 utility companies who sponsor rebates
    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
    - 100% of residents in Nevada can receive a smart thermostat for free

Contributions

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies
  - ... and utilities
    - EPA/DOE ENERGY STAR partners with 17 utility companies who sponsor rebates
    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
    - 100% of residents in Nevada can receive a smart thermostat for free
- Importance of basing decisions on field experiments, not engineering projections (Fowlie et al., 2018; Alpízar et al., 2019)

Contributions

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies
  - ... and utilities
    - EPA/DOE ENERGY STAR partners with 17 utility companies who sponsor rebates
    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
    - 100% of residents in Nevada can receive a smart thermostat for free
- 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)

Contributions

- Policy implications
  - Subsidized by government...
    - 2009-2014: DOE Smart Grid Investment Grant (SGIG) program
    - SGIG: $7.9 billion in smart tech. subsidies
  - ... and utilities
    - EPA/DOE ENERGY STAR partners with 17 utility companies who sponsor rebates
    - 20 states: $> \frac{1}{2}$ of households eligible for a rebate
    - 100% of residents in Nevada can receive a smart thermostat for free
- 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

- Individuals recruited in public places (e.g., malls, markets, & festivals)

Overview

- Individuals recruited in public places (e.g., malls, markets, & festivals)
  - Two waves: Northern & Central California
  - July 2012 - February 2013

Overview

- Individuals recruited in public places (e.g., malls, markets, & festivals)
  - Two waves: Northern & Central California
  - July 2012 - February 2013
- If eligible, randomized into treatment/control ▸ Eligibility

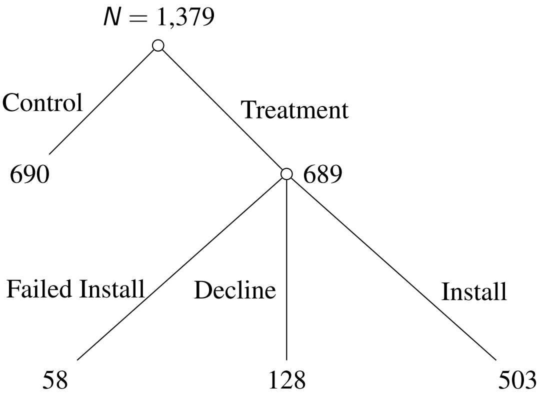
Overview

- Individuals recruited in public places (e.g., malls, markets, & festivals)
  - Two waves: Northern & Central California
  - July 2012 - February 2013
- If eligible, randomized into treatment/control Eligibility
- Treatment: smart thermostat installed at no cost

Overview

- Individuals recruited in public places (e.g., malls, markets, & festivals)
  - Two waves: Northern & Central California
  - July 2012 - February 2013
- If eligible, randomized into treatment/control Eligibility
- Treatment: smart thermostat installed at no cost
- Outcomes recorded for 18 month period
  - July 2012 - December 2013

Description of Randomization & Sample



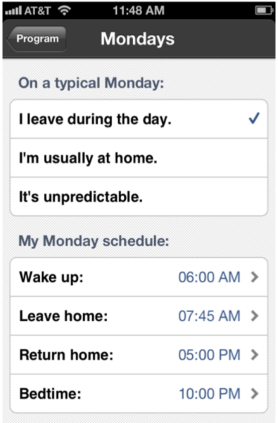
Treatment: Honeywell Z-Wave Touchscreen Smart Thermostat

Not Treatment: Honeywell Cadillac of Thermostats

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

Treatment: Smart Thermostat Features

1. Programmable schedule



Treatment: Smart Thermostat Features

1. Programmable schedule
2. Website portal & smartphone app designed/hosted by Opower

Treatment: Smart Thermostat Features

1. Programmable schedule
2. Website portal & smartphone app designed/hosted by Opower
   - Can toggle to more energy efficient setting when not home $\Rightarrow e \downarrow$
   - Don't have to get off the couch when home $\Rightarrow e \uparrow$

Treatment: Smart Thermostat Features

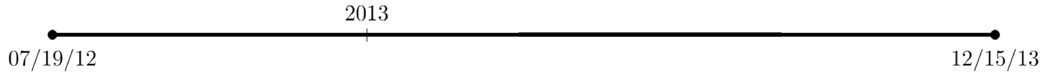
1. Programmable schedule
2. Website portal & smartphone app designed/hosted by Opower
3. Setpoint comparison analogous to Allcott (2011)

Treatment: Smart Thermostat Features

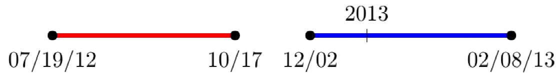
1. Programmable schedule
2. Website portal & smartphone app designed/hosted by Opower
3. Setpoint comparison analogous to Allcott (2011)
    - Descriptive norms with information on peer set point choices
    - Injunctive norms with efficiency ratings of set points

Timeline

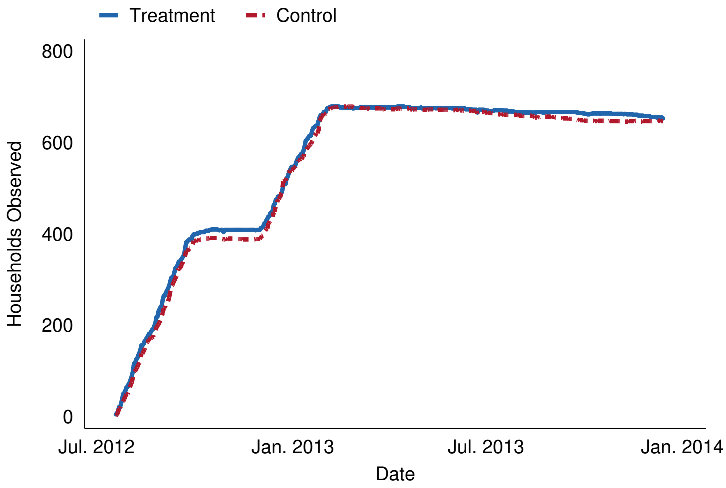
Energy Use Data



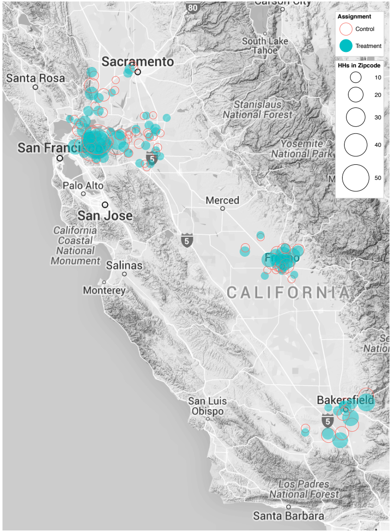
Assignment Date



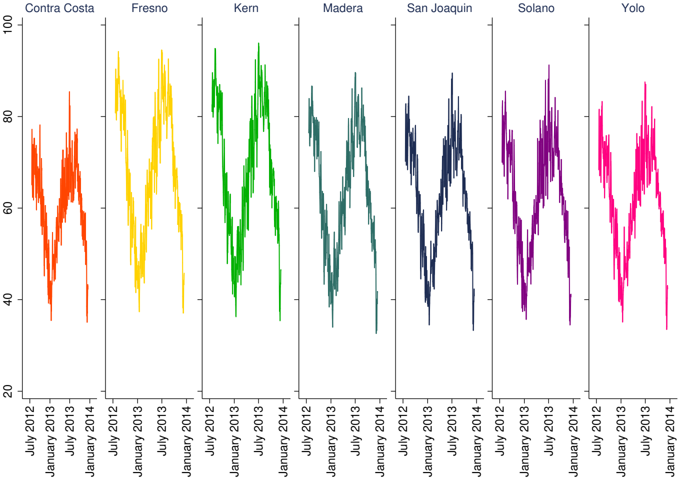
Experimental Data: Number of Households Observed by Date



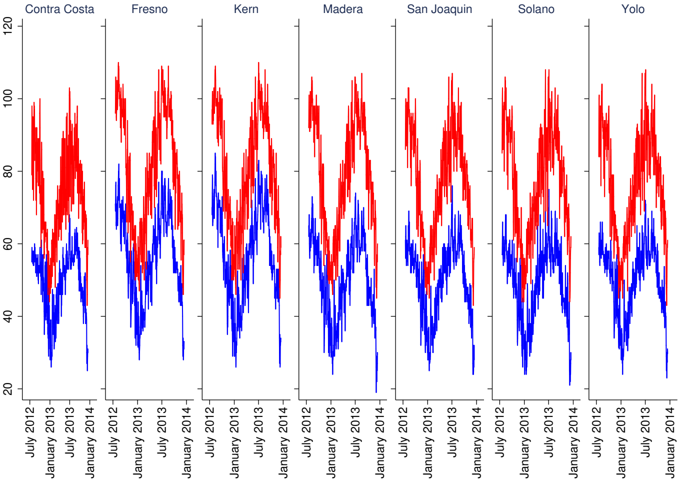
Spatial Balance



Mean Daily Temperature by County (°F)



Minimum & Maximum Daily Temperature by County (°F)



Summary Stats Table

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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			
Home Characteristics			
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
	(0.000)	(0.000)	(0.000)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Balance on Observables

Variable	All Waves $\mathbf{1}(Treated)$	Wave 1: N. CA $\mathbf{1}(Treated)$	Wave 2: C. CA $\mathbf{1}(Treated)$
Household Characteristics			
Home Characteristics			
Pre-Period Energy Use			
Mean (kWh)	-0.045*	-0.057**	-0.003
	(0.024)	(0.028)	(0.048)
Mean (thm)	-0.024	-0.008	-0.046
	(0.031)	(0.048)	(0.040)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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			
Home Characteristics			
Pre-Period Energy Use			
Mean (kWh)	-0.045*	-0.057**	-0.003
	(0.024)	(0.028)	(0.048)
Mean (thm)	-0.024	-0.008	-0.046
	(0.031)	(0.048)	(0.040)
N	1,385	821	564
R^2	0.013	0.019	0.021
F	0.731	0.822	0.687

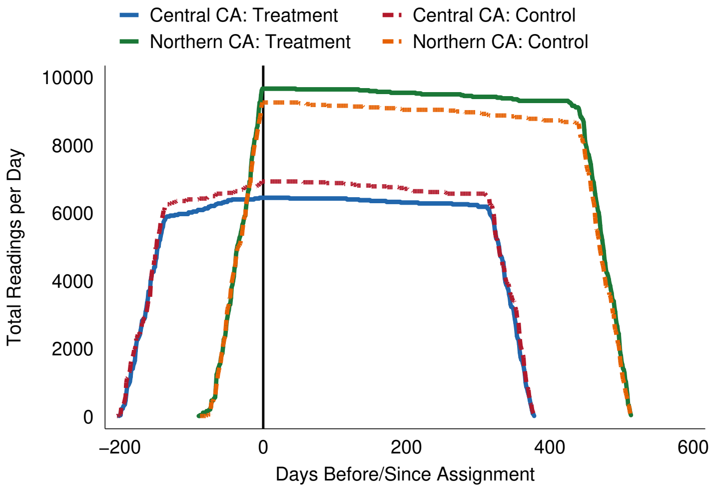
Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Balance on Observables

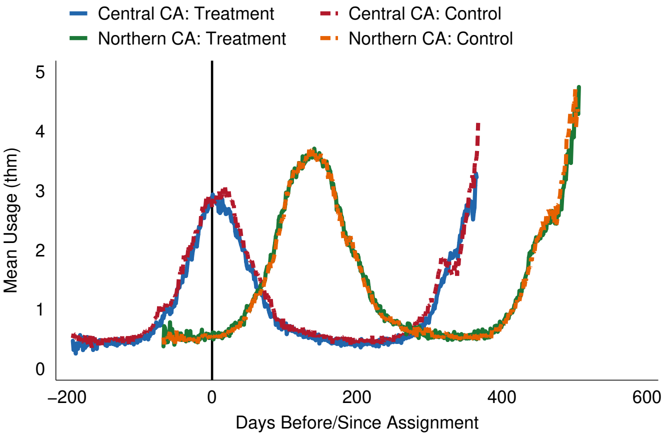
	All Waves	Wave 1: N. CA	Wave 2: C. CA
Variable	$\mathbf{1}(\mathit{Treated})$	$\mathbf{1}(\mathit{Treated})$	$\mathbf{1}(\mathit{Treated})$
Household Characteristics			
Home Characteristics			
Pre-Period Energy Use			
Mean (kWh)	-0.045*	-0.057**	-0.003
	(0.024)	(0.028)	(0.048)
Mean (thm)	-0.024	-0.008	-0.046
	(0.031)	(0.048)	(0.040)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Experimental Data: Number of Readings by Experimental Status & Wave

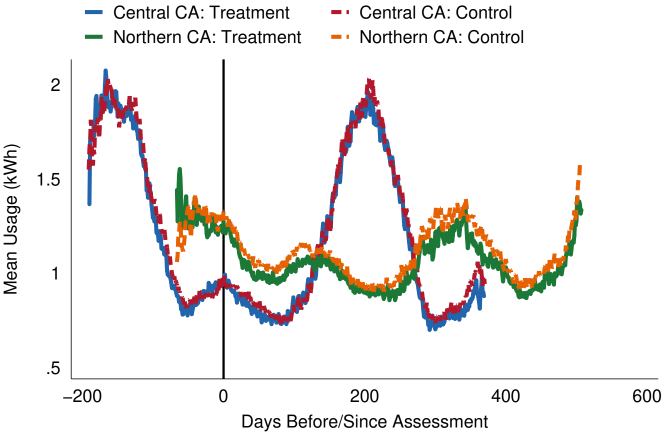


Average Natural Gas Use by Experimental Status & Wave



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

Average Electricity Use by Experimental Status & Wave



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

By Thermostat Type

Overview

- DDIV model

Overview

- DDIV model
  - Observe time series of energy use for treatment & control groups $\Rightarrow$ DD model

Overview

- DDIV model
  - Observe time series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Self selection after randomization? $\Rightarrow$ IV model

Overview

- DDIV model
  - Observe time series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Self selection after randomization? $\Rightarrow$ IV model
- e_{it}^{j} is energy use of type j
  - i indexes households
  - t indexes time period
  - $j \in$ {electricity, natural gas}

Overview

- DDIV model
  - Observe time series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Self selection after randomization? $\Rightarrow$ IV model
- e_{it}^{j} is energy use of type j
  - i indexes households
  - t indexes time period
  - $j \in$ {electricity, natural gas}
- 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
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable

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
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable

- Two-stage least squares (2SLS) estimation with

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

  - $Z_{it}^j = \left(\alpha_i^j, \beta_t^j, T_i P_t, X_{it}\right)'$
  - T_i is an indicator for household i's treatment status in our experiment

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
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable
- Two-stage least squares (2SLS) estimation with

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

  - $Z_{it}^j = \left(\alpha_i^j, \beta_t^j, T_i P_t, X_{it}\right)'$
  - T_i is an indicator for household i's treatment status in our experiment

Interpretation of γ^j

- Under the assumptions of
  - Instrument exogeneity

Interpretation of γ^j

- Under the assumptions of
  - Instrument exogeneity
  - One-sided noncompliance
    - Some households in treatment do not install 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

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

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

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

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

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

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

1. Main (all waves)
    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

1. Main (all waves)
    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
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
	(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
	(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
	(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 * $p < 0.1$.

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)
	$< 35\ °F$	$35 - 49\ °F$	$50 - 64\ °F$	$65 - 79\ °F$	$> 80\ °F$
	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)
	$< 35\ ^\circ F$	$35 - 49\ ^\circ F$	$50 - 64\ ^\circ F$	$65 - 79\ ^\circ F$	$> 80\ ^\circ F$
	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) Quintile 1	(2) Quintile 2	(3) Quintile 3	(4) Quintile 4	(5) 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) Quintile 1	(2) Quintile 2	(3) Quintile 3	(4) Quintile 4	(5) 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)

Threats to ID

- Treated may not install a smart thermostat quickly (slow-compliance)
  - Time to installation is short

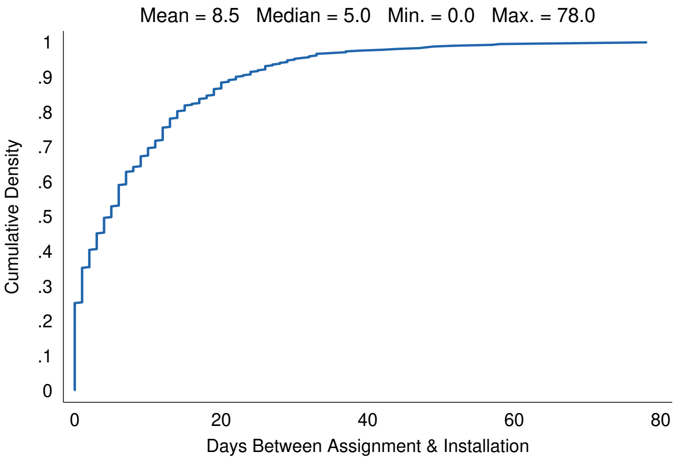
Threats to ID

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

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

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)

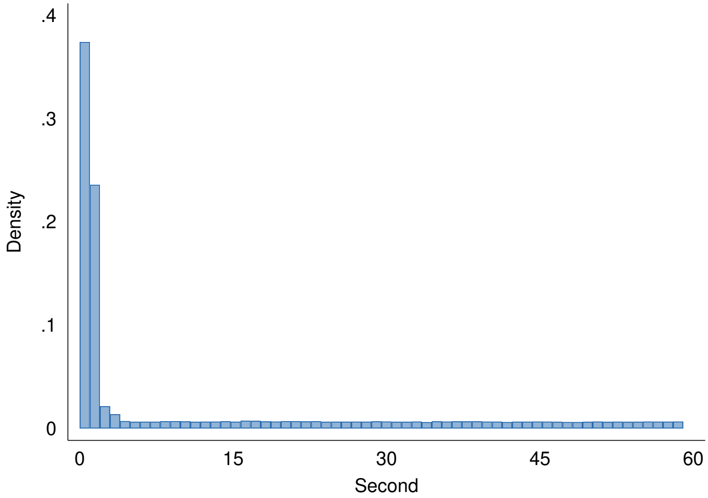
Events Data Description

- Observe: exact time of HVAC events
  - Ambient temperature
  - Temperature settings
  - HVAC state (heating, cooling, fan)
- Do not observe: type of temperature setting
  - Permanent setpoints or
  - Temporary overrides

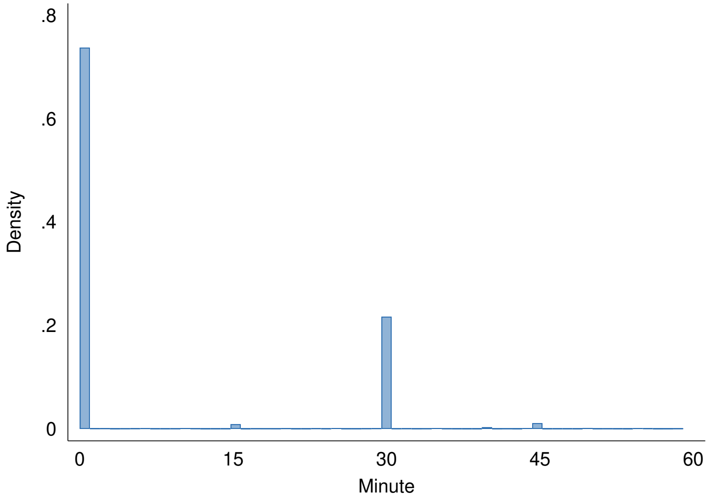
Events Data Description

- Observe: exact time of HVAC events
  - Ambient temperature
  - Temperature settings
  - HVAC state (heating, cooling, fan)
- Do not observe: type of temperature setting
  - Permanent setpoints or
  - Temporary overrides
  - $\Rightarrow$ Code settings occurring at 00-02 seconds as setpoints

Density of Temperature Changes by Second of the Minute



Density of Permanent Setpoints by Minute of the Hour



Events Data Description

- Observe: exact time of HVAC events
  - Ambient temperature
  - Temperature settings
  - HVAC state (heating, cooling, fan)
- Do not observe: type of temperature setting
  - Permanent setpoints or
  - Temporary overrides
  - $\Rightarrow$ Code settings occurring at 00-02 seconds as setpoints

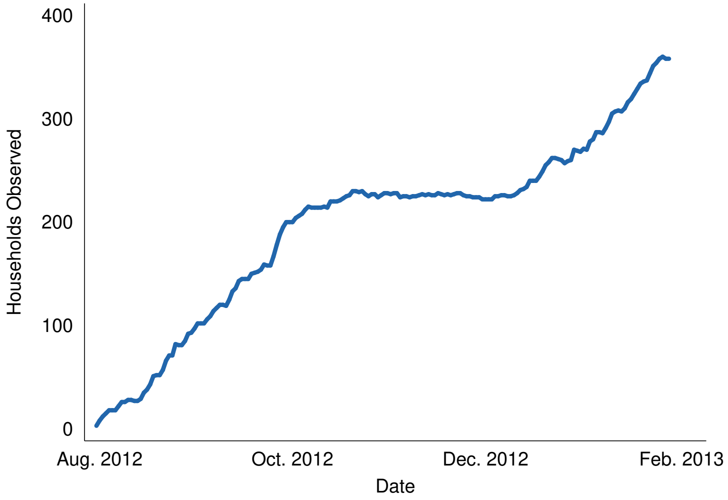
Events Data Description

- Observe: exact time of HVAC events
  - Ambient temperature
  - Temperature settings
  - HVAC state (heating, cooling, fan)
- Do not observe: type of temperature setting
  - Permanent setpoints or
  - Temporary overrides
  - $\Rightarrow$ Code settings occurring at 00-02 seconds as setpoints
- Do not observe: events data for all installer households/time periods
  - $\Rightarrow$ Focus on best match to experimental data (N. CA, Natural Gas)

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	

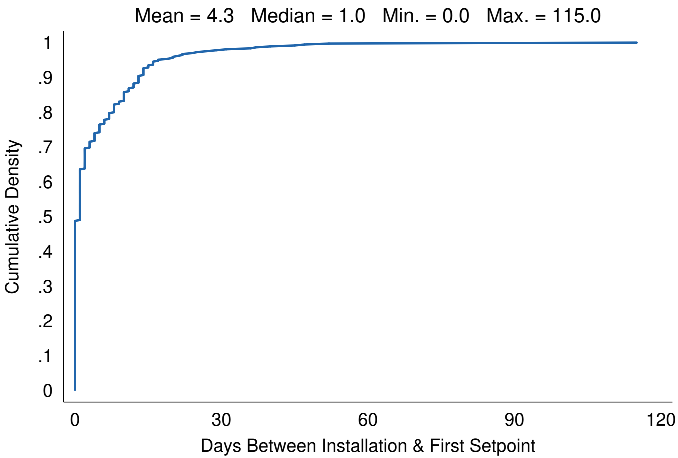
Events Data: Number of Households Observed by Date



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?

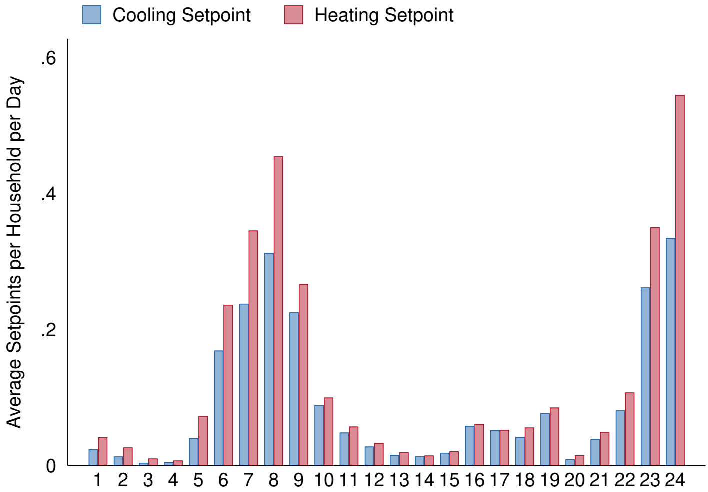
Distribution of Time from Installation to First Permanent Setpoint



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

Breakdown

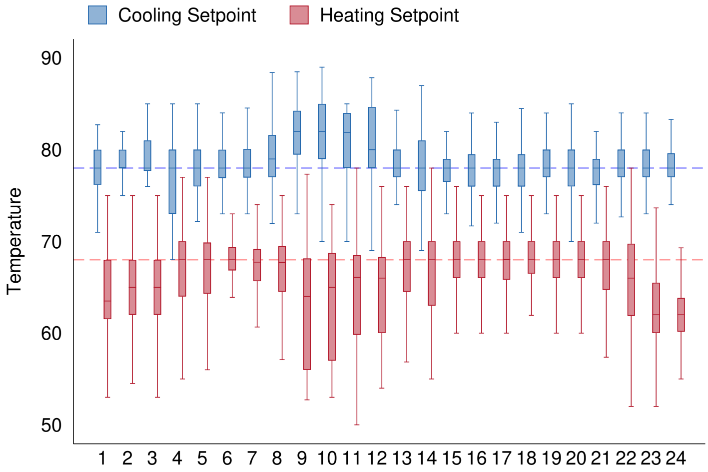
Average Permanent Setpoints per Household per Day by Hour



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?

Box & Whisker Plots of Permanent Setpoints by Hour

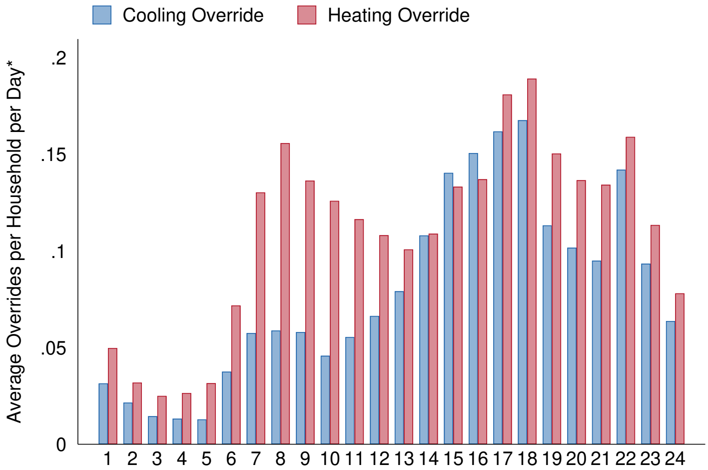


Dashed lines represent EPA recommended cooling/heating settings.

Outline

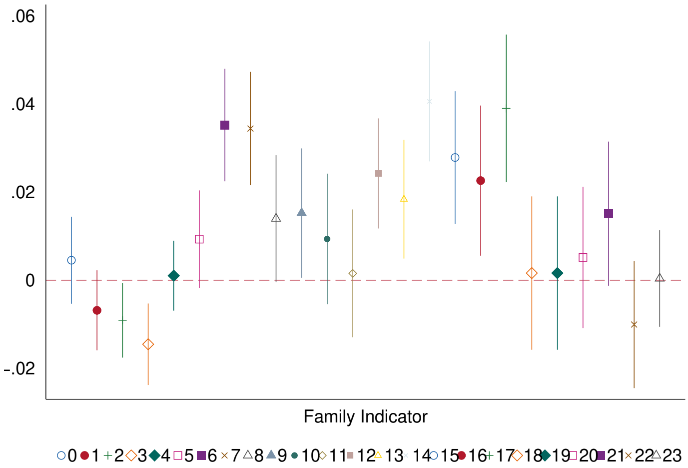
1. HVAC events data description ✓
2. Potential mechanisms
    1. Do users program their smart thermostats? ✓
    2. Do users program their smart thermostats for energy savings? ✓
    3. Do users deviate from their programed schedules?
    4. Do user deviations increase or decrease energy use?
    5.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

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 1(Override) by Hour

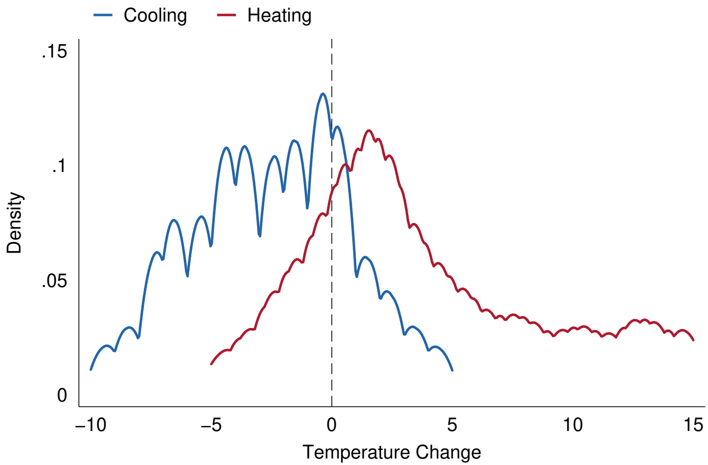


Setpoints Analysis

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?

Density of Override & Setpoint Temperature Differences by HVAC State



Densities truncated at the 5th and 95th percentiles.

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? $\uparrow$ 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

Estimation of Effects by Energy-Efficiency Type

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

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

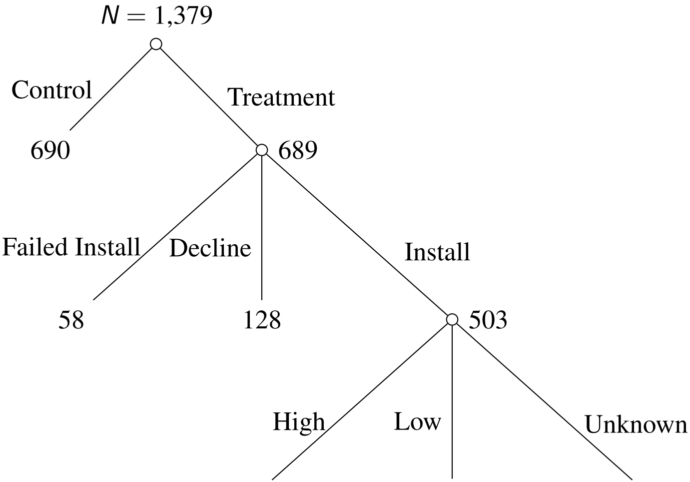
Estimation of Effects by Energy-Efficiency Type

- 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

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?

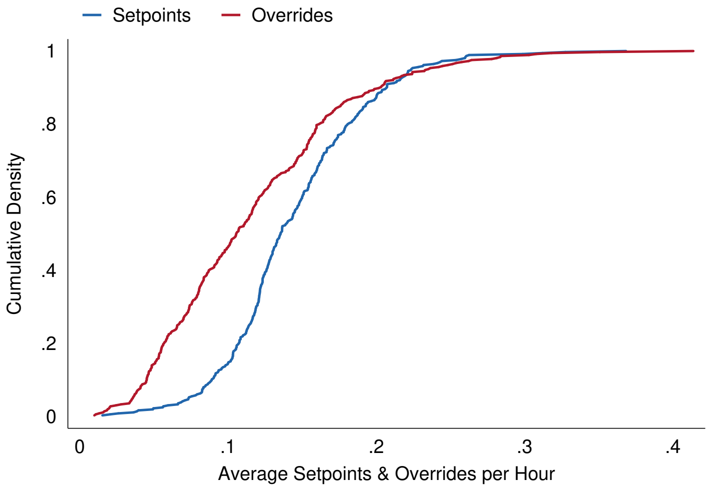
Description of Randomization & Sample



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

Model Overview

- Difference-in-differences intention-to-treat (DDITT) model
  - Observe time-series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Interact type w/ treatment, but no IV for type $\Rightarrow$ ITT model

Model Overview

- Difference-in-differences intention-to-treat (DDITT) model
  - Observe time-series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Interact type w/ treatment, but no IV for type $\Rightarrow$ ITT model
- e_{it}^{j} is energy use of type j
  - i indexes households
  - t indexes time period
  - $j \in$ {electricity, natural gas}
  - $k \in$ {high, low, ?}

Model Overview

- Difference-in-differences intention-to-treat (DDITT) model
  - Observe time-series of energy use for treatment & control groups $\Rightarrow$ DD model
  - Interact type w/ treatment, but no IV for type $\Rightarrow$ ITT model
- e_{it}^{j} is energy use of type j
  - i indexes households
  - t indexes time period
  - $j \in$ {electricity, natural gas}
  - $k \in$ {high, low, ?}
- Estimate e_{it}^{j} 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

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

  - T_i is an indicator for household i's treatment status in our experiment
  - R_i^k 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_i^j is a household fixed effect
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable
- γ_k^j is the ITT effect of a smart thermostat on energy j for households of type k

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.

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.

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.

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.

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					
	(0.037)					
$\hat{\gamma}^{thm}_{High}$		0.067	-0.060	-0.063	-0.077*	-0.089**
		(0.144)	(0.078)	(0.057)	(0.046)	(0.041)
$\hat{\gamma}^{thm}_{Low}$		-0.085**	-0.072	-0.078	-0.032	0.423***
		(0.042)	(0.046)	(0.050)	(0.071)	(0.080)
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.

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					
	(0.037)					
$\hat{\gamma}^{thm}_{High}$		0.067	-0.060	-0.063	-0.077*	-0.089**
		(0.144)	(0.078)	(0.057)	(0.046)	(0.041)
$\hat{\gamma}^{thm}_{Low}$		-0.085**	-0.072	-0.078	-0.032	0.423***
		(0.042)	(0.046)	(0.050)	(0.071)	(0.080)
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.

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					
	(0.037)					
$\hat{\gamma}^{thm}_{High}$		0.067	-0.060	-0.063	-0.077*	-0.089**
		(0.144)	(0.078)	(0.057)	(0.046)	(0.041)
$\hat{\gamma}^{thm}_{Low}$		-0.085**	-0.072	-0.078	-0.032	0.423***
		(0.042)	(0.046)	(0.050)	(0.071)	(0.080)
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.

Potential Mechanisms Summary

- Evidence that users do use the features of their smart thermostats
  - Program their thermostats well
  - Deviate from their programed schedules

Potential Mechanisms 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

Potential Mechanisms 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

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

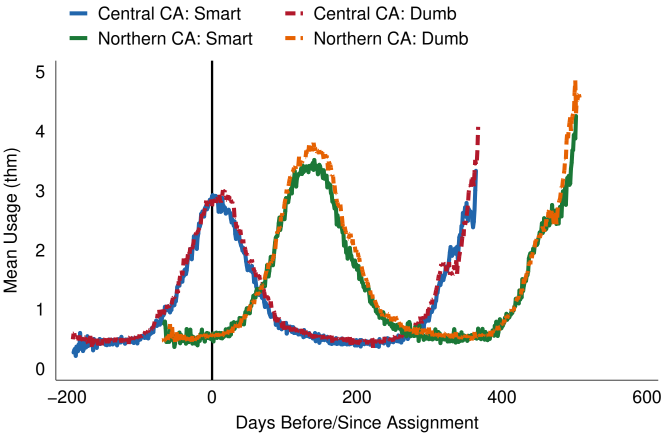
Return

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			

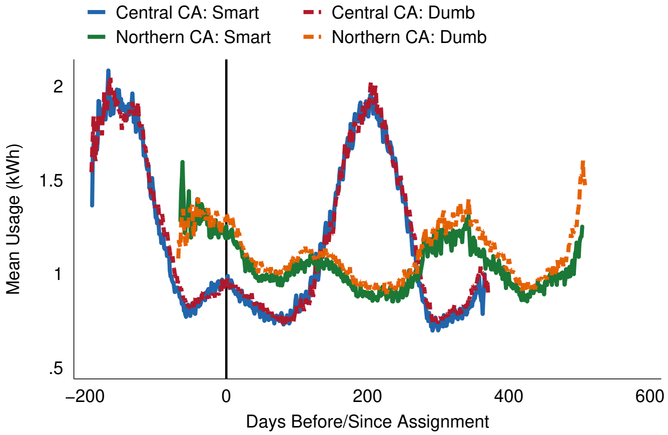
Return

Average Natural Gas Usage by Thermostat Type & Wave



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

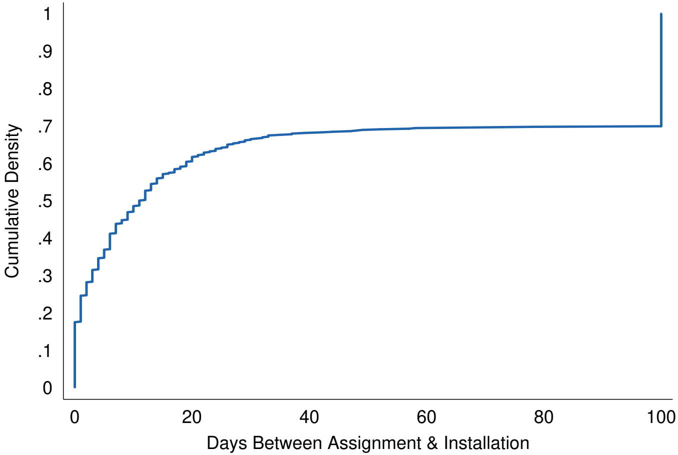
Average Electricity Usage by Thermostat Type & Wave



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

Return

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
  - α_i^j is a household fixed effect
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable
- Two-stage least squares (2SLS) estimation with

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

  - $Z_{it}^j = \left(\alpha_i^j, \beta_t^j, T_i P_t, X_{it}\right)'$
  - T_i is an indicator for household i's treatment status in our experiment

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
  - α_i^j is a household fixed effect
  - β_t^j is a time effect
  - X_{it} is a vector of controls
  - u_{it}^j is a household/time varying unobservable
- Two-stage least squares (2SLS) estimation with

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

  - $Z_{it}^j = \left(\alpha_i^j, \beta_t^j, T_i P_t, X_{it}\right)'$
  - T_i is an indicator for household i's treatment status in our experiment

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)	(2)	(3)	(4)	(5)
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	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

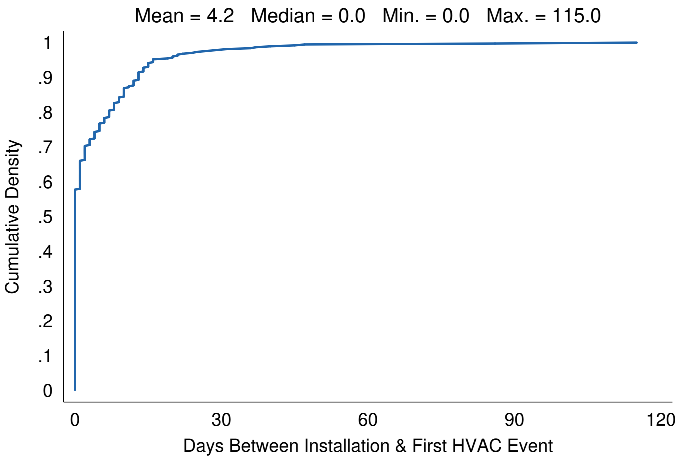
Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

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

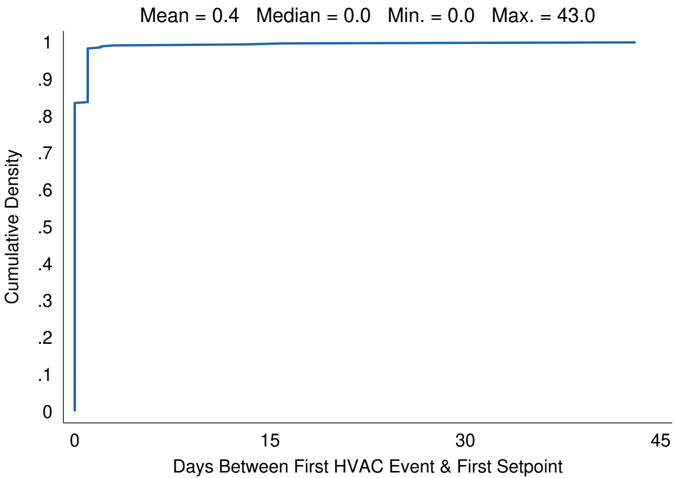
Note: Standard errors in parentheses are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

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

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

	(1) Baseline	(2) 10	(3) 30	(4) 50	(5) 70	(6) 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)

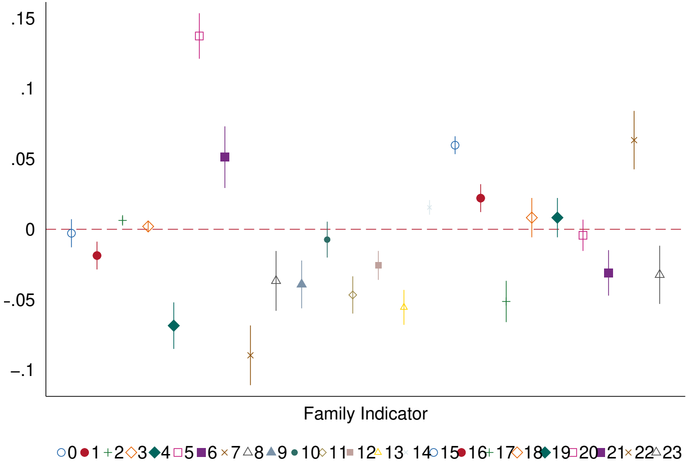
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	20	30	50	70	90
				Power Use (thm)		
$\hat{\gamma}^{kWh}$	-0.001					
	(0.017)					
$\hat{\gamma}^{kWh}_{High}$		-0.009	-0.043	-0.001	0.001	-0.002
		(0.044)	(0.035)	(0.027)	(0.024)	(0.022)
$\hat{\gamma}^{kWh}_{Low}$		-0.015	-0.006	-0.022	-0.036	-0.073
		(0.023)	(0.024)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

Do Families Program More Setpoints?



Return

References I

Allcott, Hunt, "Social norms and energy conservation," *Journal of Public Economics*, 2011, *95* (9), 1082 – 1095. Special Issue: The Role of Firms in Tax Systems.

Alpízar, Francisco, María Bernedo, and Paul J. Ferraro, "Input Efficiency as a Solution to Externalities: Engineers vs Behavioral Scientists in a Randomized Controlled Trial," Technical Report 2019.

Burkhardt, Jesse, Kenneth Gillingham, and Praveen K Kopalle, "Experimental Evidence on the Effect of Information and Pricing on Residential Electricity Consumption," Working Paper 25576, National Bureau of Economic Research February 2019.

Cornelissen, Thomas, Christian Dustmann, Anna Raute, and Uta Schönberg, "From LATE to MTE: Alternative Methods for the Evaluation of Policy Interventions," *Labour Economics*, 2016, *41*, 47 – 60. SOLE/EALE conference issue 2015.

References II

Energy Information Administration, "Energy Consumption and Expenditures Tables," Technical Report, U.S. Department of Energy, 2015 Residential Energy Consumption Survey May 2018.

_ , "Annual Energy Outlook 2019 with Projections to 2050," Technical Report, U.S. Department of Energy, Office of Energy Analysis January 2019.

_ , "Monthly Energy Review," Technical Report, U.S. Department of Energy, Office of Energy Statistics August 2019.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram, "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program*," *The Quarterly Journal of Economics*, 01 2018, *133* (3), 1597–1644.

Tufano, Fabio and John A. List, "On the Importance of 'Null Effects' in Economics," 2019.