Understanding Energy Efficiency Benefits from Smart Thermostats in Southern California

BECC Conference - Dec 2014

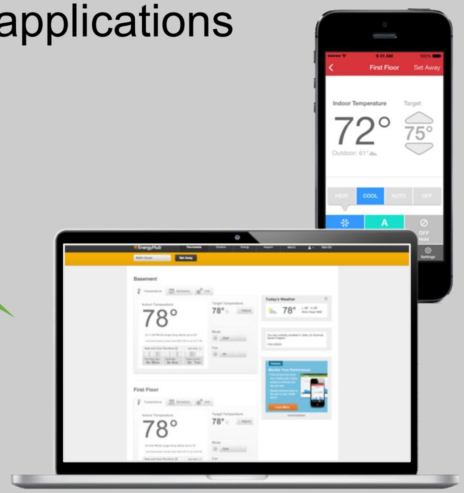
Ben Ho

EnergyHub and Vassar College

30K data points per thermostat per month

Customers access EH apps more than once a day

Engaging consumer web and mobile applications



Any connected device

Utility management and analytics application

Real-time, precision forecasting
Robust M&V system

EnergyHub®

My research program :
Behavioral Economics and Climate Change

- 2011 Vassar and EnergyHub — Smart Thermostats (Big Data, Habit)
- 2010 BECC — Do Cold Prickles Induce Warm Glows (Guilt)
- 2008 BECC — Using Behavioral Economics to Save the World (Carbon Offsets)
- 2007 Cornell — Fairness, Inequality, Identity
- 2006 White House CEA — Lead Energy Economist
- 2001 Stanford GSB — PhD Dissertation : Apologies (Classmates Annika Todd)

Preview of Findings

Combined hourly meter readings with smart thermostat usage data for 89 California households that adopted a smart thermostat between summers 2012 and 2013

Smart thermostats <u>reduce overall electricity bills by 6</u>% in summer months (an average savings of $15.60 per month)

Savings were largest in August, when savings were 17%. Also largest in afternoons and early in the week.

Preview of Findings (more)

Our model controls for outdoor weather, household characteristics, and seasonal effects.

We find learning as well. Those who make the most use automated set points saw an additional 10% reduction in electricity usage.

Greatest savings come from highest energy use households (highest quartile).

Mechanisms

-  Procrastination
-  Transaction costs
-  Attention
-  Habit
-  Learning
-  Novelty seeking

Description of the Devices

- Minute by minute thermostat readings of indoor and outdoor temperature and set point coupled with hourly weather data and utility provided meter data.
- Can be programmed to change the setpoint **automatically** by time of day and day of week.
- Users can **override** the program using the thermostat or a smartphone app or a webpage **(median user overrides once a day)**.

Literature Review: Smart Thermostats

- Giving users more information about energy use and more control reduces heating/cooling demand (Faruqui and Sergici, 2010; Dulleck and Kaufmann 2000)
- Utilities like Smart Thermostats for Demand Side Management (DSM) reducing energy usage during peak demand periods.
- Changing thermostats are costly. Ease of use of Thermostat affects frequency of use. (Peffer et al 2011)
- Market For Smart Thermostats \$149 million (2013) projected to be \$2.3 billion in (2023) (Navigant Research)
- 2% of homes (Forrister Research)

Summary Statistics

Variables	2012 Mean (Stdev)	2013 Mean (Stdev)
Hourly Meter Reading (Wh)	1409 (1485)	1221 (1337)
Mean Target Temperature (degrees F)	78 (8.9)	75 (12.2)
Outdoor Temperature (degrees F)	76 (11.3)	75 (10.9)

Statistical Model

- Performed Linear Regression Analysis
  - Robustness checks included panel analysis, robust standard errors clustered by household, and non-linear / polynomial regression discontinuity (discussed later)

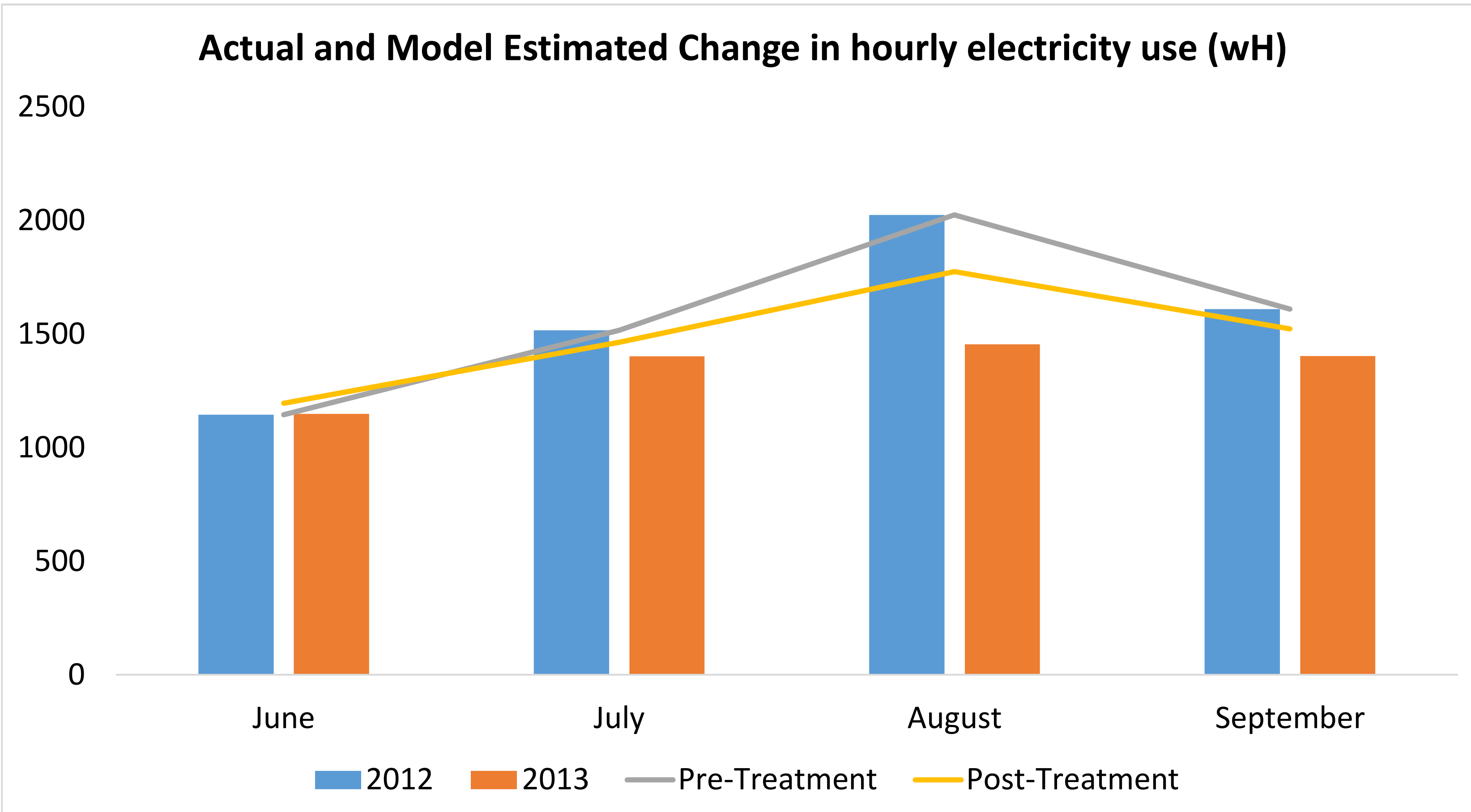
$$Y_{i,t} = \alpha \cdot \mathbb{I}_{treated} + \boldsymbol{\beta} \cdot \boldsymbol{X}_{controls} + \varepsilon_{i,t}$$

  - Dependent Variable is hourly meter reading for each household I
  - Treated is an indicator for adoption of smart thermostat.

- Included Controls for
  - Prevailing weather
  - Month of year, time of day, day of week
  - Household characteristics

Identification Strategy:
Based on comparing same day 2012 vs same day 2013 on days where that household did not have the smart thermostat in 2012 but did in 2013.

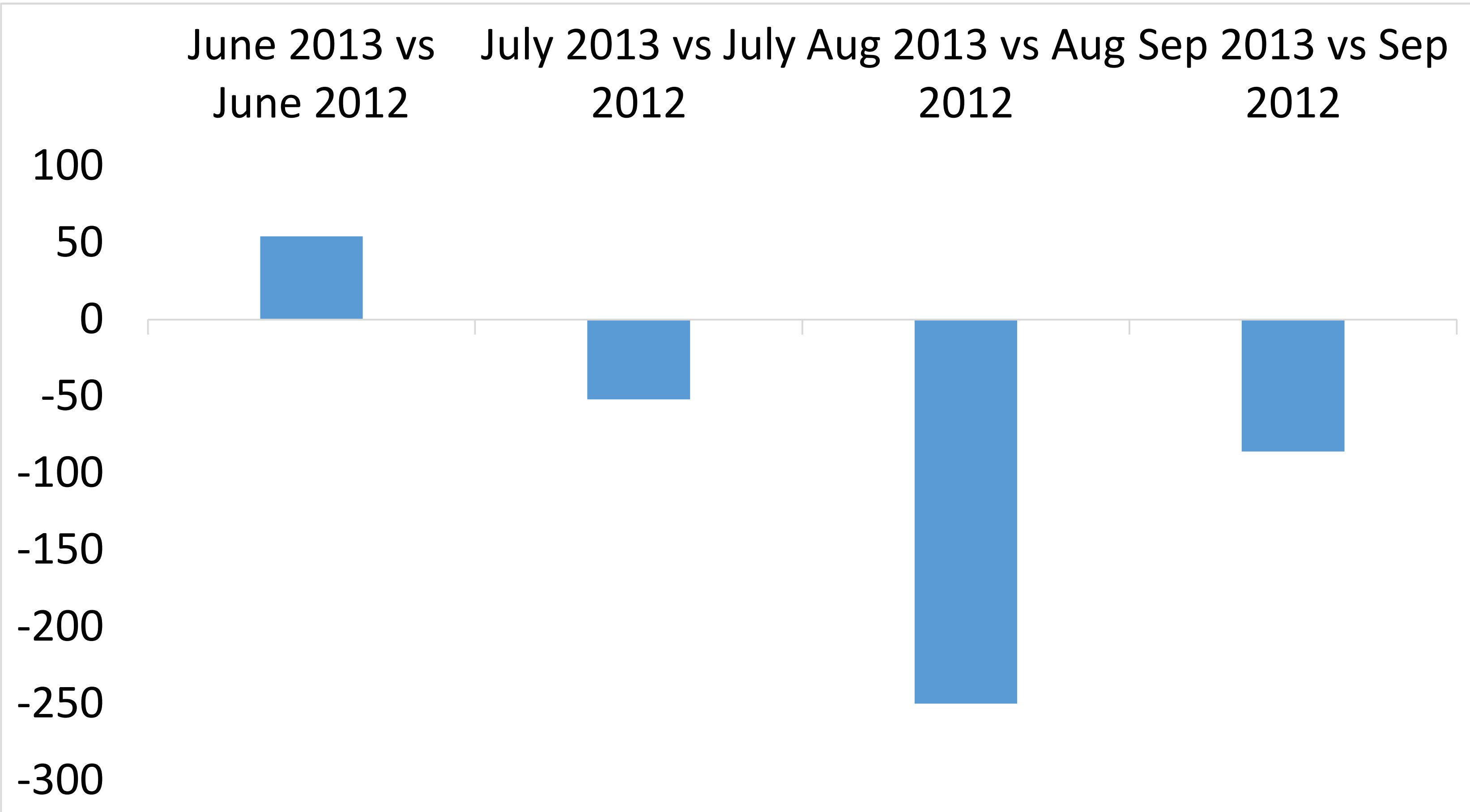
Main Result
(actual in bars, predicted in levels)



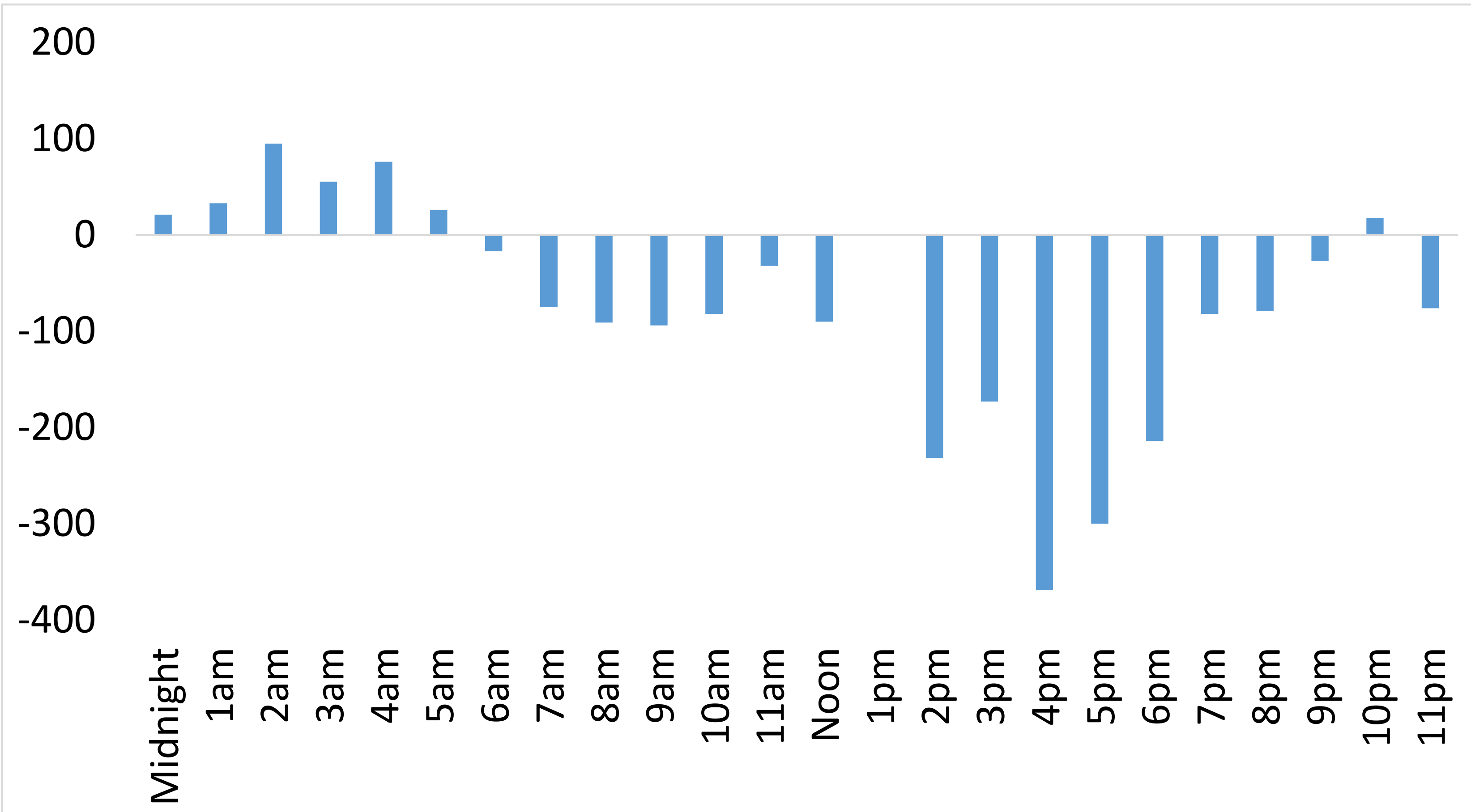
Locus of Savings

Month, Day, Time, Household Size

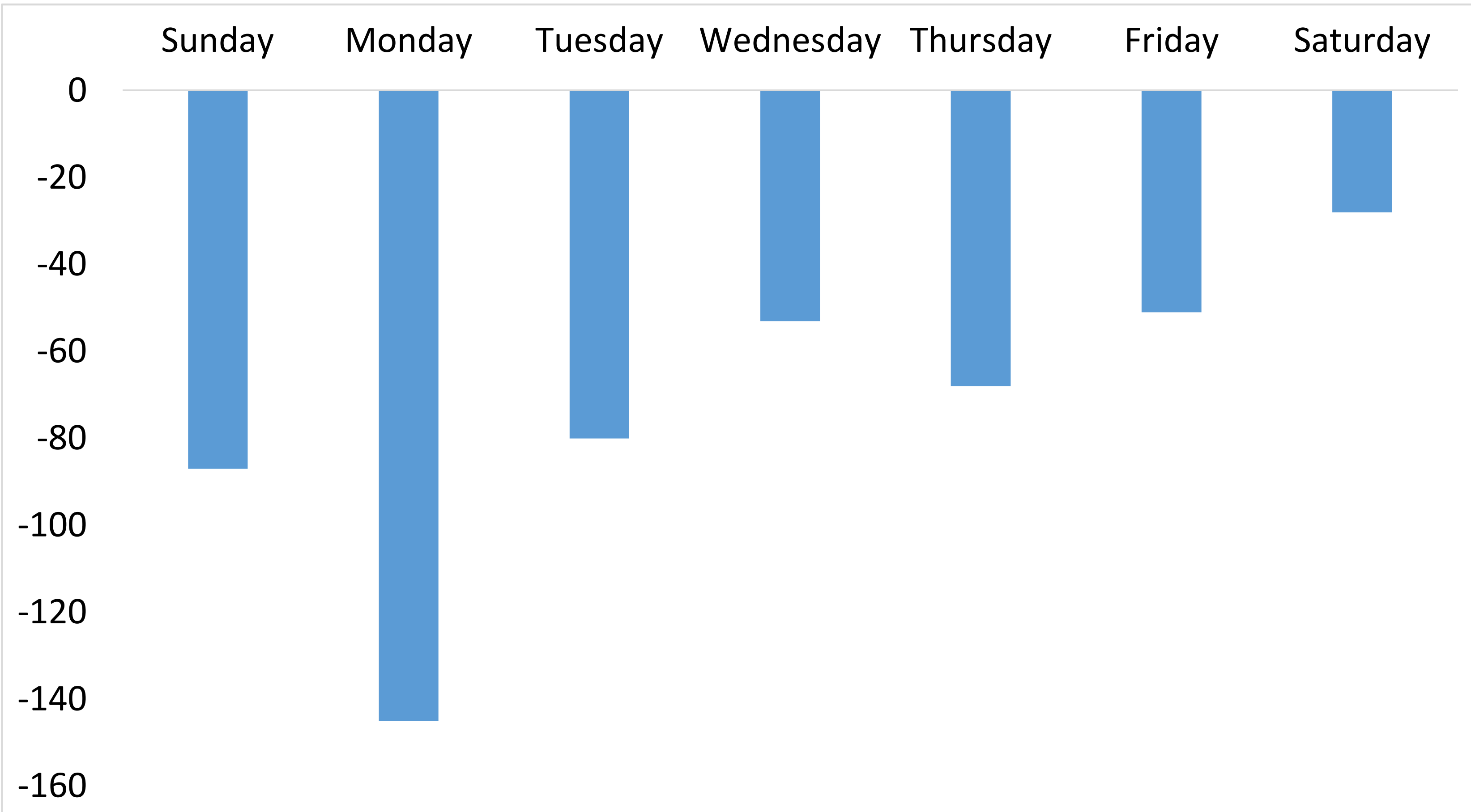
Month to Month Comparisons in Wh/hour
(negative numbers indicate savings)



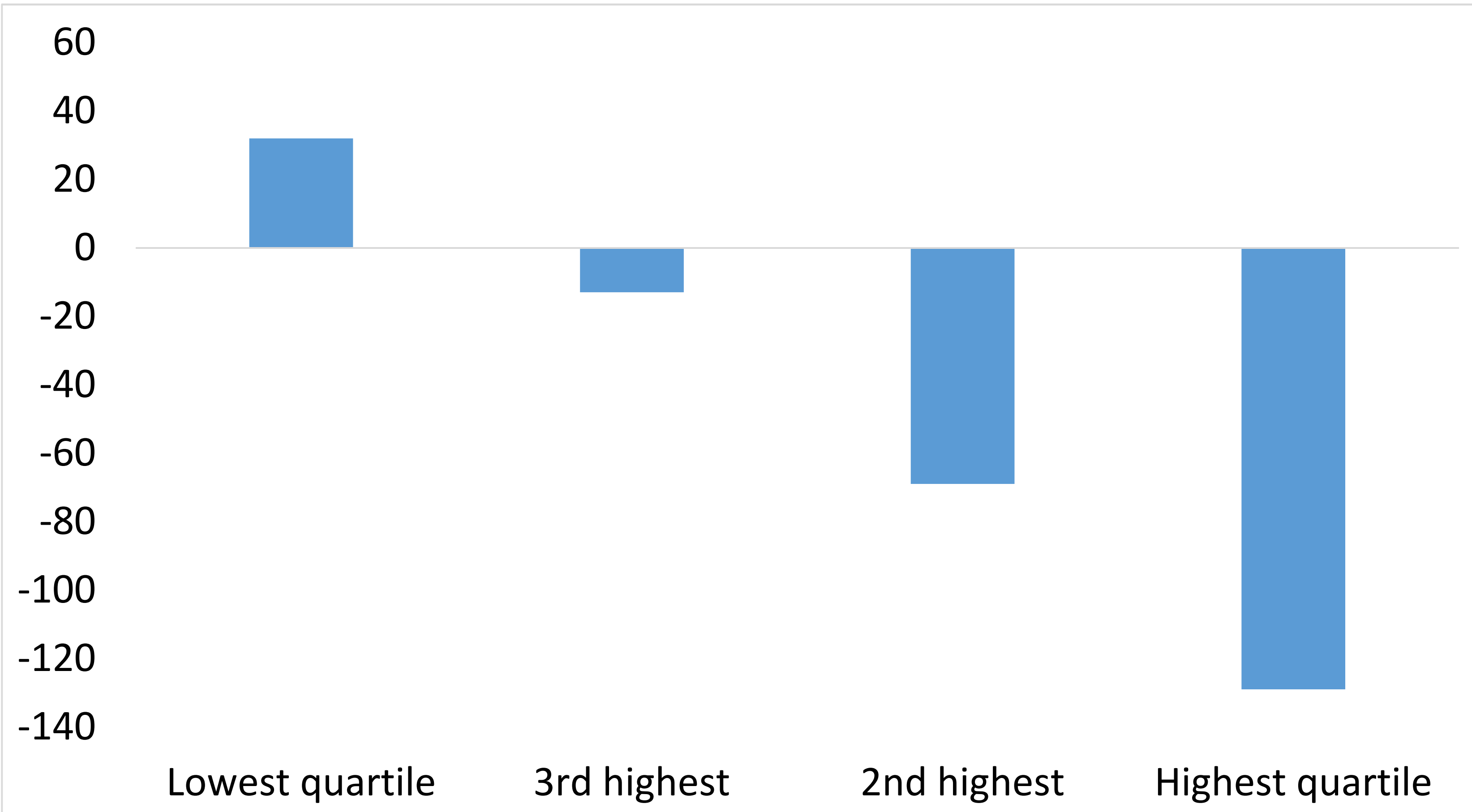
Time of Day Comparisons in Wh/hour (Negative numbers indicate savings)



Day of Week Comparisons in Wh/hour (negative numbers indicate savings)



Savings by household size in Wh per hour (negative numbers indicate savings)



Robustness Check

Decomposing the Savings

Robustness Check

- Although we control for
  - Prevailing weather
  - Month of year, time of day, day of week
  - Date of thermostat adoption
  - Household characteristics

- Two concerns remain
  - **Omitted Variable Bias** (although omitted variable would have to also predict same patterns of savings)
  - **No Within Year Savings** (RD design), Only Between Year

Decomposing the Savings

How much of the savings can be explained by:

- The **mean level of the set point**.
- The **difference** between the level of the set point and the outdoor temperature.
- The **standard deviation of the set point** (a measure of the number of adjustments made to the set point both automatic and user controlled).
- **Set point unpredictability** (changes that can't be predicted by time of day or day of week).

Decomposing the Savings:
Statistical Model

- Added interaction terms of the regression framework

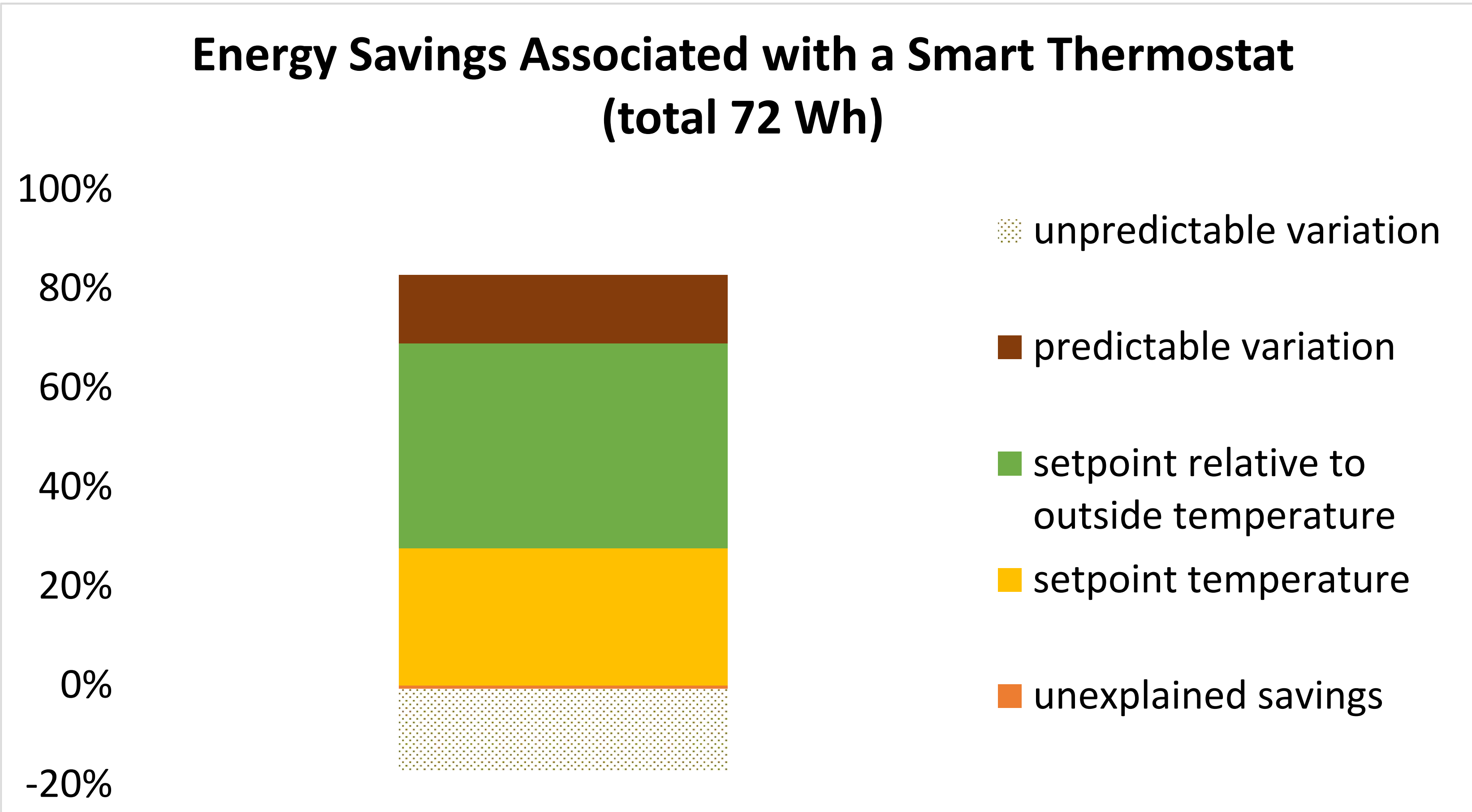
$$Y_{i,t} = \alpha \cdot \mathbb{I}_{treated} + \boldsymbol{\beta} \cdot \boldsymbol{X}_{controls} + \boldsymbol{\gamma} \cdot \mathbb{I}_{treated} \cdot \boldsymbol{Z}_{interaction} + \varepsilon_{i,t}$$

- Decomposed the treatment effect by interacting with:
    - Mean set point
    - difference with outdoor temperature
    - predictable variation of setpoint
    - unpredictable variation of set point

- Still Included Controls for
    - Prevailing weather
    - Month of year, time of day, day of week
    - Household characteristics

- *Note while main results hold up with clustered standard errors, we do not have enough households for these decompositions to be significant when errors are clustered.*

Decomposing the Savings
(total 72 Wh per hour)



Decomposing the Savings: Takeaways

- Most of the energy savings correlated with installation of the thermostat was due to their thermostat usage.
  - The choice of temperature set point explains nearly all of the savings;
  - **Supports hypothesis that impact is causal, not just correlated**.
- Unpredictable variation of set point settings leads to increased energy use
  - Households that had more unpredictable adjustments (as owners **fiddled** with the settings) saw their energy use increase.
  - Households that had more predictable variation (following a program according to hour of day) saw their energy use decrease.

Concluding Thoughts

(and preview of Big Data)

Mechanisms

-  Procrastination
-  Transaction costs
-  Attention
-  Habit
-  Learning
-  Novelty seeking

Concluding Thoughts

Main Ideas

- Found 6% savings during summer months in 89 California households from smart thermostat adoption
- Locus of Savings in high usage households, during high usage months (August), during afternoon hours, and on Mondays
- Savings only arise after learning period

Limitations

- 89 households is limiting
- Cannot fully rule out other behaviors correlated with thermostat adoption.

Other Work

- Impact of Price Information
- Analysis of Habit

Extra Slides

Energy Consumption and Habit Formation:

Evidence from High Frequency Thermostat Data

Qi Ge
Skidmore College

Benjamin Ho
Vassar College

Main Points

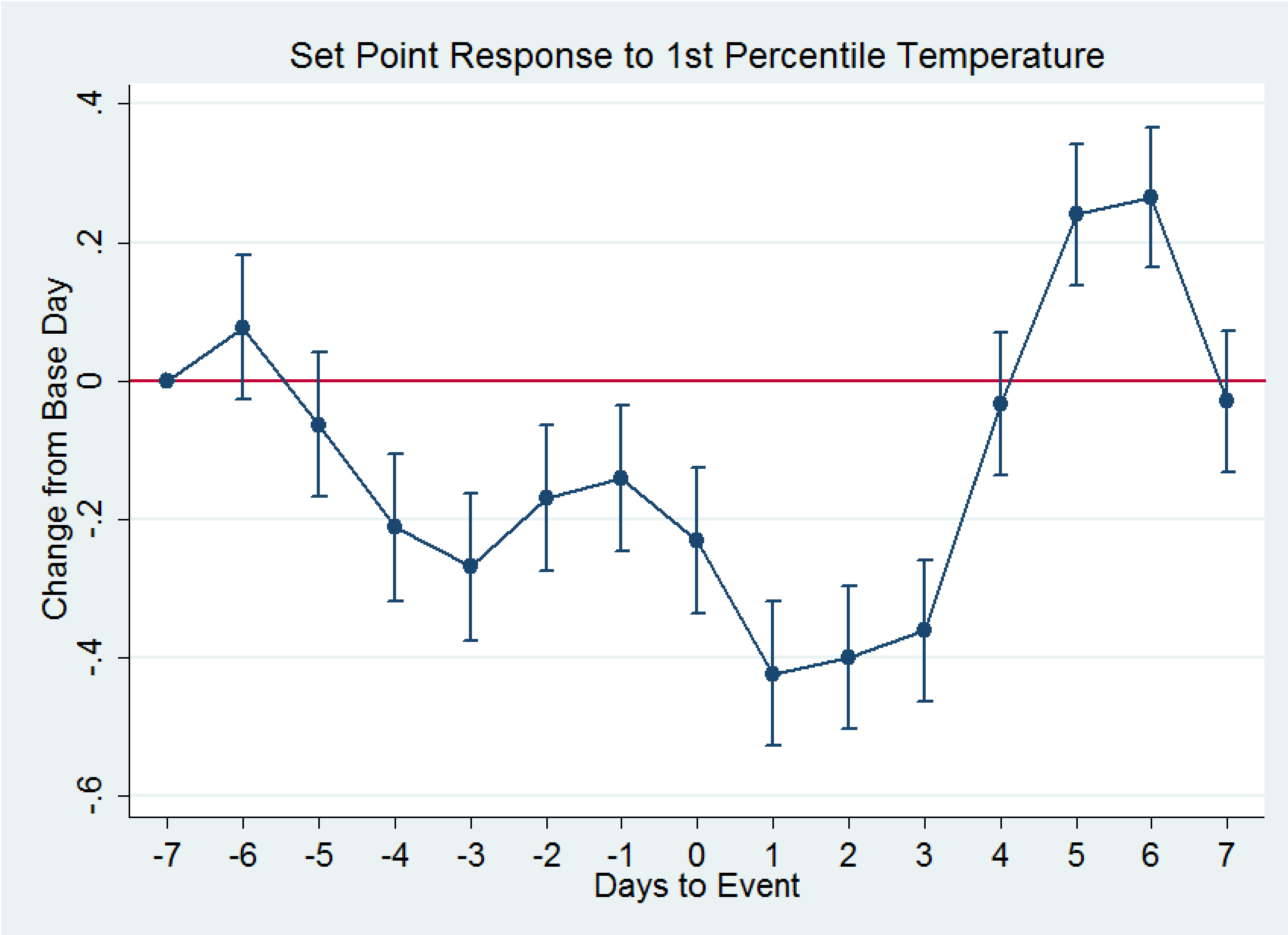
- (BIG DATA) Dataset of 60,000 households
  - Observed every minute for 27 months, recording indoor and outdoor temperature, set point, and program settings
- Paper tests and estimates theories of habituation
  - Habituation
  - Homeostasis
  - Cue Salience
  - Social Norming
- Main findings:
  - Energy consumption affected by external cues in both short run and long run
  - Habituation for moderate temperatures, but homeostasis for extreme weather and repeated extreme weather.
  - Habituation in the short run, but returns to homeostasis after 2-3 days.
  - Evidence projection bias
  - Little evidence of choice satiation
  - Social norms may matter

Discussion

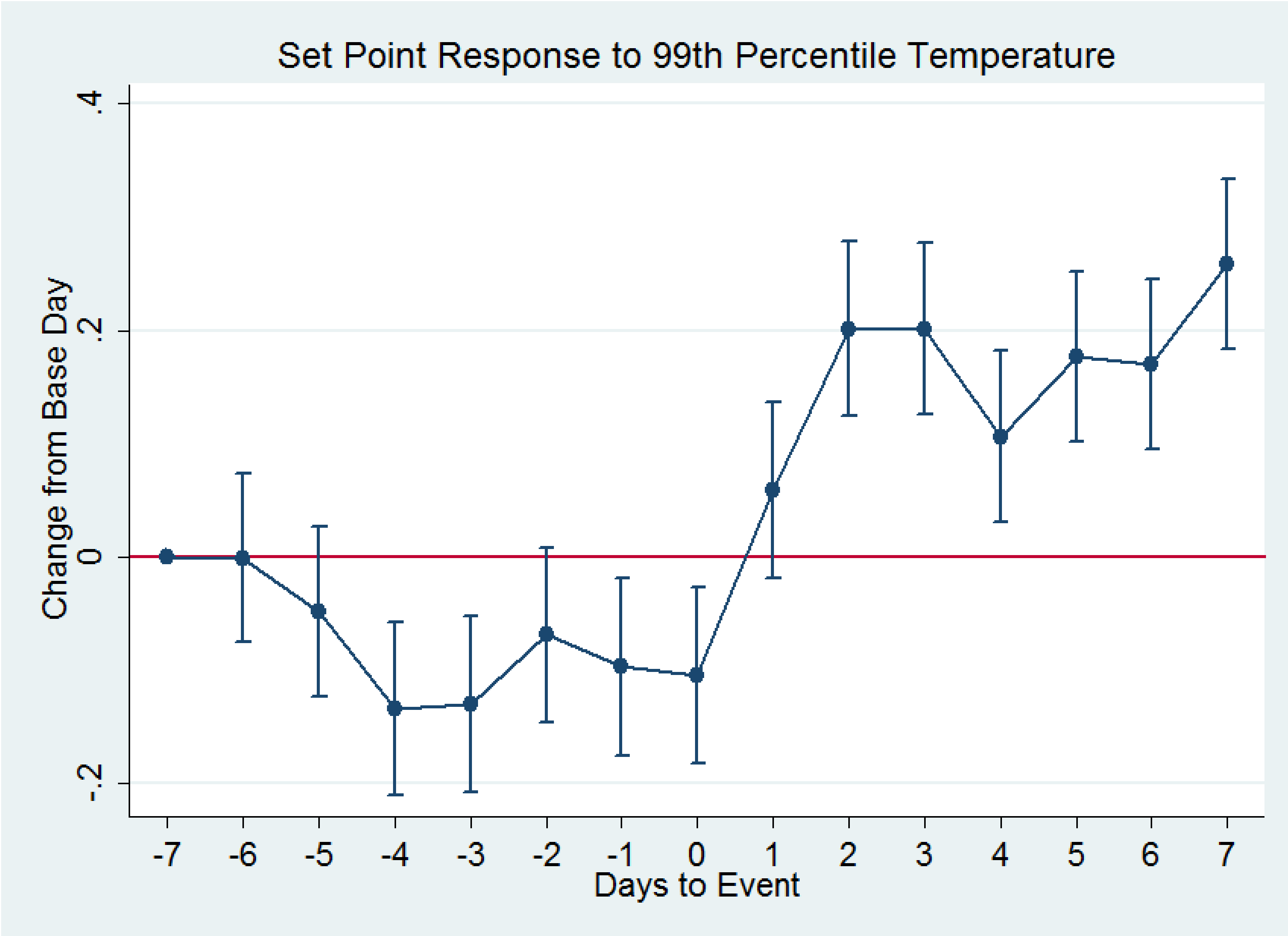
- Implications for understanding the **long run** impact of **interventions**
- Important for understanding the difference between **moderate interventions** vs. **extreme interventions**
- Important for understanding the difference between **one shot interventions** versus **repeated interventions**
- Implications for understanding long run versus short run **estimates of elasticities**
- Implications for understanding the **social dependencies** of interventions

	(1)	(2)	(3)	(4)
		Meter Reading (kWh)		
Energy Savings	-72.49***	2.526	2.013	5.257
	(4.114)	(6.261)	(6.270)	(6.270)
… explained by set point		-1.470***	-1.372***	-1.470***
		(0.0867)	(0.106)	(0.106)
… explained by temp difference		-6.732***	-6.841***	-7.044***
		(0.207)	(0.218)	(0.219)
… explained by overall set point variation			-1.258	-7.447***
			(0.787)	(0.970)
… explained by hourly set point variation				8.156***
				(0.745)
Outdoor temperature	41.80***	38.15***	38.08***	37.97***
	(0.281)	(0.305)	(0.308)	(0.308)
month controls	yes	yes	yes	yes
day of week controls	yes	yes	yes	yes
time of day controls	yes	yes	yes	yes
household controls	yes	yes	yes	yes
Observations	416,154	416,154	416,154	416,154
R-squared	0.362	0.364	0.365	0.365

Standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**



Set Point Response to 1st Percentile Temperature
Change from Base Day
.4
.2
0
-.2
-.4
-.6
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
Days to Event


Set Point Response to 99th Percentile Temperature
Change from Base Day
.4
.2
0
-.2
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
Days to Event