Digital Dispatch and Demand Response in Grid Emergencies: Evidence from Household Cooling in California's Flex Alerts

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School of Economics

Extreme heat and aging infrastructure stresses the grid

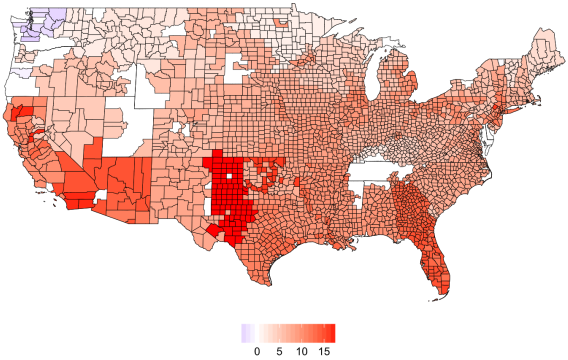
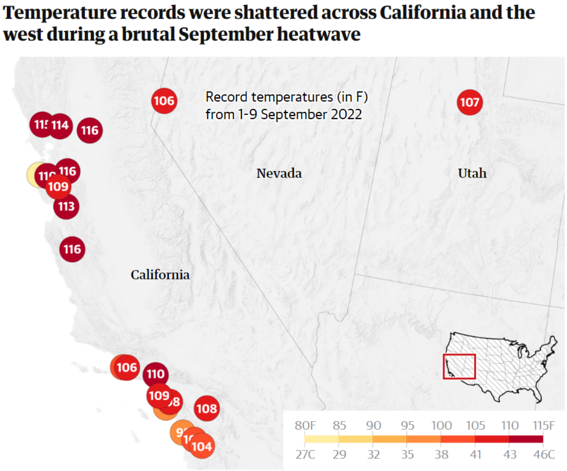


Fig. 3. Projected change in intensity of peak load (RCP8.5). The projected change in intensity of peak load under RCP8.5 varies geographically, with the largest increases in the South and West. Coloring reflects projected percentage increases in the daily peak load due to temperature rise by end of century.

Source: Auffhammer et al. 2017



Source: theguardian.com

How to curb electricity consumption when a blackout is likely?

1. Demand response (DR)
    - Dynamic pricing (Fu, Novan, and Smith, 2024; Burkhardt, Gillingham, and Kopalle, 2023; Ito, Ida, and Tanaka, 2018)
    - Its combination with automation (Bailey et al., 2025; Blonz et al., 2025; Bollinger and Hartmann, 2020)
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2. Moral suasion
   (Brewer and Crozier, 2025; He and Tanaka, 2023; Holladay, Price, and Wanamaker, 2015)
   - Rely on the salience of the message and behavioral mechanisms such as warm glow (Andreoni, 1989), social pressure (DellaVigna, List, and Malmendier, 2012), or moral payoff of contributing to public goods (Levitt and List, 2007; Ferraro and Price, 2013; Allcott and Kessler, 2019)

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→ While recent works find that automation bypasses human inattention, it is still unclear how this automation performs alongside moral suasion during an actual emergency

We focus on Flex Alerts during a brutal September heatwave in 2022

Flex Alerts recommend specific cooling setpoints:

- Before peak period: 70°F
- During peak period: 78°F

Communication campaigns via social media and private email and text (*only if customers sign-up*)

In parallel, CAISO often called DR events within the peak period for customers enrolled in automated DR programs

‣ Detail on grid condition during September 2022 heatwaves

Source: X.com

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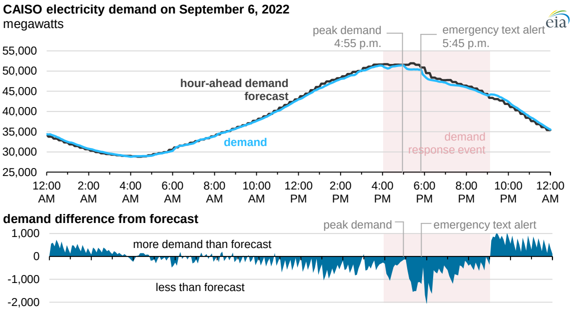

Source: EIA

‣ Detail on grid condition during September 2022 heatwaves

We focus on Flex Alerts during a brutal September heatwave in 2022

Flex Alerts repeteadly issued for ten consecutive days

CalOES sent a high-salience emergency alert sent on September 6th to all cell phones in California

This sequence of events provides rich variation:

- **policy instrument across households**
  (voluntary conservation vs. automated DR)
- **salience over time**
  (low-salience vs. post emergency phone alert)

▸ Detail on grid condition during September 2022 heatwaves

Day 1 of 10, 3 hours before Flex Alert

Source: X.com

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Day 1 of 10, 1 hour before Flex Alert

Source: Youtube.com

Detail on grid condition during September 2022 heatwaves

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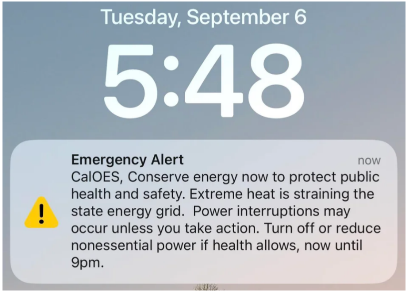
Day 7 of 10, 2 hours within Flex Alert



Source: Davis 2022

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Day 8 of 10

CALIFORNIA

A text asked millions of Californians to save energy. They paid heed, averting blackouts

After narrowly avoiding blackouts, California faces another bruising test of its power grid Thursday as a heat wave smothering the region builds, driving temperatures to dangerous levels. (Eric Thayer / Bloomberg via Getty Images)

BY GRACE TOOHEY, ALEXANDRA E. PETRI

SEPT. 7, 2022 UPDATED 8:30 PM PT

Source: LATimes.com

This Paper

How does automated demand response performs alongside moral suasion during an actual emergency?

This Paper

Empirical results:

1. Salience plays a central role in voluntary conservation
2. Automated DR consistently outperforms voluntary conservation
3. Salience and automation interact in a complementary way

Welfare implications:

1. Demand reductions are substantial ($\approx$ 1,300 MW)
2. Automated DR programs contributed less than 10 percent of the total reductions
3. Primary value of emergency conservation is grid reliability in avoiding blackouts

Contributions to existing literature

- We identify distinct behavioral dynamics: habituation, reactivation, and inattention.
  - Behavioral responses to resource scarcity (Deryugina, 2017; Dinerstein et al., 2025; Reiss and White, 2008; Costa and Gerard, 2021; He and Tanaka, 2023)
  - Dynamics of behavioral intervention in energy economics (Ito, Ida, and Tanaka, 2018; Allcott and Rogers, 2014; Fowlie et al., 2021; Costa and Gerard, 2021)

- We demonstrate that crisis salience and automation operate as complements during grid emergencies
  - Automation and demand response scarcity (Bollinger and Hartmann, 2020; Bailey et al., 2025; Blonz et al., 2025)
  - Smart technology and human behavior (Prest, 2020; Brandon et al., 2022)

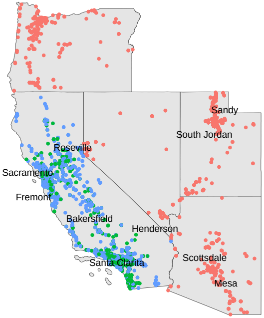
- We provide a comprehensive welfare analysis of emergency conservation
  - Economics of emergency energy conservation (Brewer and Crozier, 2025; He and Tanaka, 2023; Holladay, Price, and Wanamaker, 2015)
  - Welfare effects of energy conservation (Ito, Ida, and Tanaka, 2018; Allcott and Kessler, 2019; Jacob et al., 2023; Bollinger and Hartmann, 2020)

We use smart thermostat data from Ecobee Donate Your Data

Main outcomes: Cooling setpoint and compressor run-time for each household

▸ Pre and post for outcome variables

- Originally in 5-minute intervals aggregated to hourly, covering Aug 1st - Sept 25th
- We use the self-reported location (city) to match weather station data from Visual Crossing
- We exclude households with missing location or extreme setpoints ($< 40°$F or $> 100°$F)



- Treatment group: CA households
  - 5,180 non-DR households
  - 3,319 DR households

  ▸ Detail on identifying DR households

- Control group: NV, AZ, OR, UT households
  - 3,706 non-DR households

▸ Trends in outcome variables between treatment and control group

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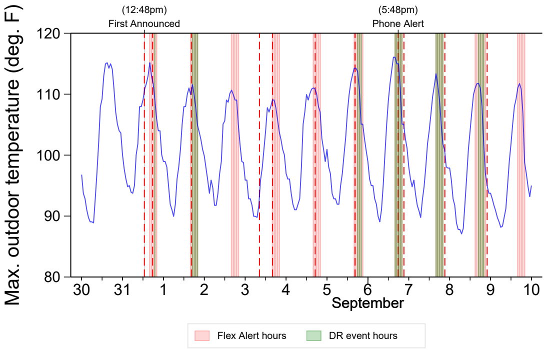


- Variation in salience due to the phone alert:
  - Low salience Flex Alerts: 8/31 - 9/5
  - Higher salience Flex Alerts: 9/6 - 9/9
- Variation in DR events for DR participants within peak hours:
  - automated thermostat override
  - conservation incentives

Estimating the effect of Flex Alerts and DR events

We employ a generalized difference-in-difference design:

ATT low-sal. Flex Alerts — ATT low-sal. DR events

$$y_{ith} = \sum_{k=0}^{2} \beta_{FA,k} \left(D_{ith} \times \mathbb{1}[Period_h = k]\right) + \delta_{FA} \left(D_{ith} \times \mathbb{1}[Period_h = 1] \times \mathbb{1}[DRevent_{ith}]\right)$$
$$+ \sum_{k=0}^{2} \beta_{PA,k} \left(P_{ith} \times \mathbb{1}[Period_h = k]\right) + \delta_{PA} \left(P_{ith} \times \mathbb{1}[Period_h = 1] \times \mathbb{1}[DRevent_{ith}]\right) + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}$$

ATT high-sal. Flex Alerts — ATT high-sal. DR events

y_{ith}: outcomes for household i at day t and hour h,
D_{ith} =1 for CA after Flex Alert, P_{ith} =1 for CA after Phone Alert, $DREvent_{ith}$ =1 for CA when in DR event,
$k = \{$Before-Peak, Peak, After-Peak$\}$, X_{ith}: weather controls, α_{ith}: household $\times$ hour $\times$ day and hour-of-sample FEs

Summary of Findings

#1 Salience plays a central role in voluntary conservation.

#2 Automated DR consistently outperforms voluntary conservation.

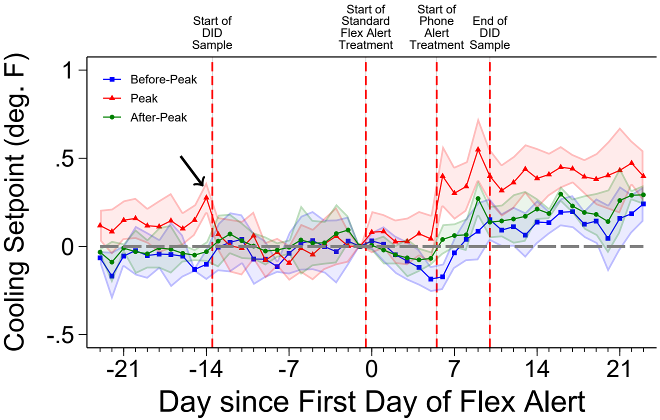
#3 Salience and automation interact in a complementary way.

‣ Results on other outcome variables

	(1) Cooling Setpoint	(2) Compressor Run-Time
After First Tweet		
Before-Peak	-0.086***	0.210
	(0.021)	(0.224)
Peak	0.035	-0.266
	(0.029)	(0.641)
Peak $\times \mathbb{1}$ (DR Event)	0.358***	-0.182
	(0.120)	(0.661)
After-Peak	-0.085***	0.736
	(0.024)	(0.501)
After Phone Alert		
Before-Peak	0.001	-0.808
	(0.025)	(0.627)
Peak	0.304***	-0.780
	(0.077)	(0.658)
Peak $\times \mathbb{1}$ (DR Event)	1.069***	-1.991**
	(0.128)	(0.854)
After-Peak	0.043	2.238**
	(0.035)	(0.993)
No. of Household	11,807	12,135
Observations	6,342,016	6,632,642

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors follow Driscoll and Kraay (1998)

Result #1: Salience plays a central role in voluntary conservation



We extend our sample beyond the DID sample to include more lead and lag coefficient

Panel fixed effects: Event study ‣ Event study on other outcome variables ‣ Event study using only DID sample

$$y_{ith} = \sum_{t\in[-23,23],t\neq-1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t\in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

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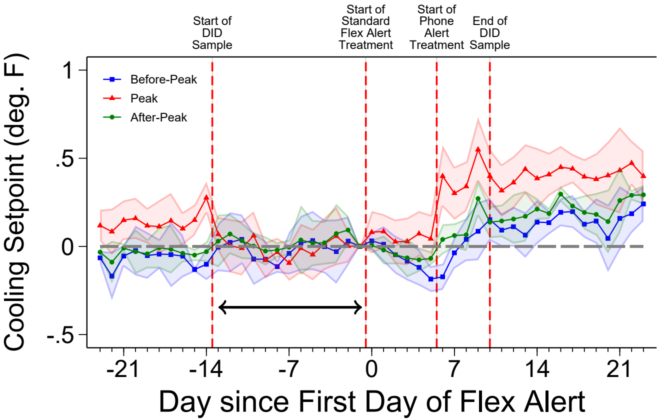

We extend our sample beyond the DID sample to include more lead and lag coefficient

We find statistical evidence of a parallel trend in our pretreatment period

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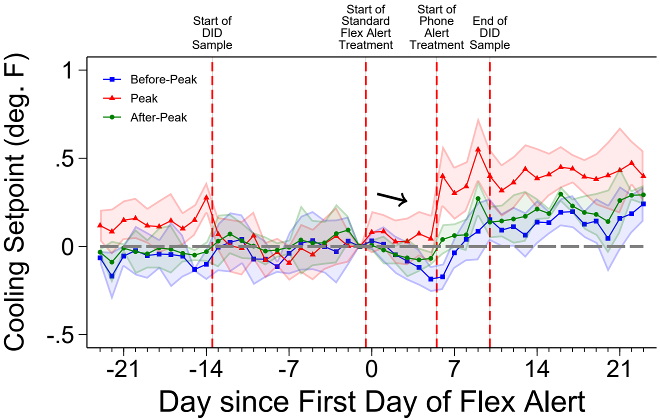

We find suggestive evidence of habituation during a standard Flex Alerts

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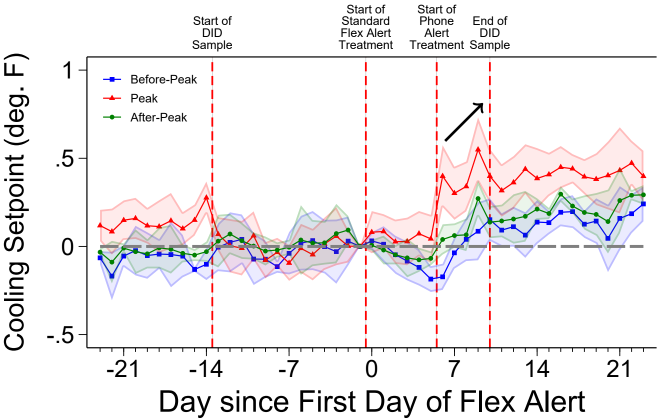

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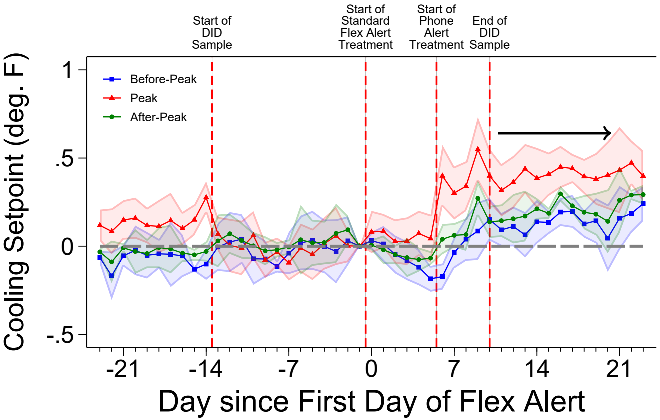

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The phone alert reactivates household responses, and the effect gets larger as they receive more Flex Alerts

The treatment effect stays for two weeks, even though there is no longer a grid emergency (hysteresis/inattention)

Panel fixed effects: Event study ▸ Event study on other outcome variables ▸ Event study using only DID sample

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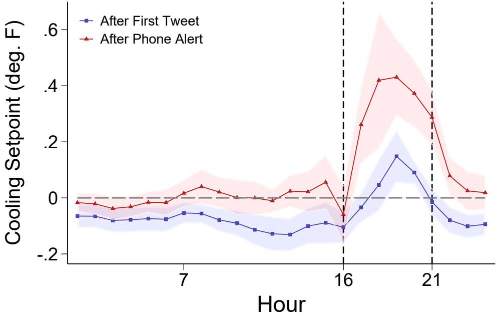
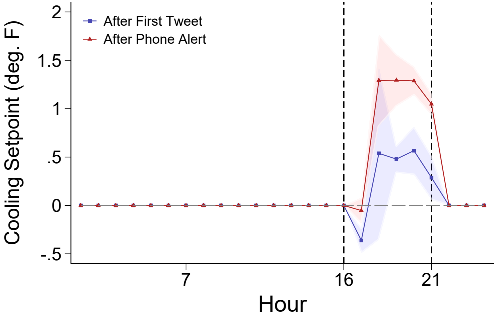
Result#2: Automated DR consistently outperforms voluntary conservation

The effect of Flex Alerts vs DR events





▸ Hourly effect on other outcome variables

- Low salience DR cause ↑ 0.5 °F, greater than Flex Alerts with high salience
- The DR events immediately affect cooling behavior within an hour

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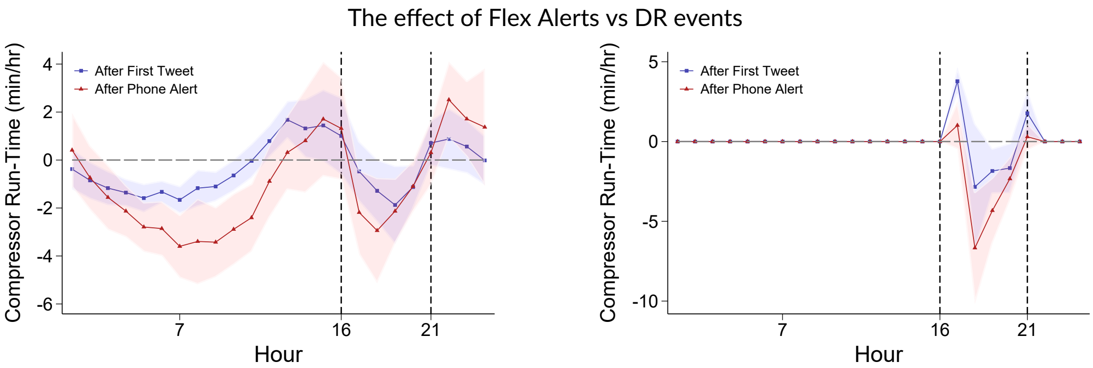

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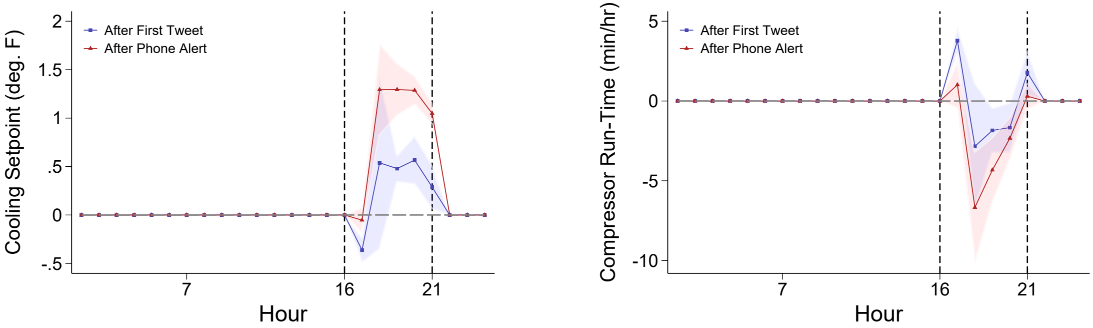
Result #3: Salience and automation interact in a complementary way

The effect of DR events on Cooling Setpoint and Compressor Run-Time



▸ Hourly effect on other outcome variables

- In low salience: setpoint ↑ 0.5 °F, and in high salience: setpoint ↑ 1.3 °F more
- Reduction of compressor run-time from DR increase by $3\times$ after phone alert

Model of thermostat setpoint behavior

- **First stage** (Brewer and Crozier, 2025): Households choose baseline setpoints to maximize:

$$U_0(T, p) = u(T) - px(T)$$

  $u(T)$ is utility or comfort from choosing a cooling setpoint ($\partial u/\partial T \leq 0$, $\partial^2 u/\partial T^2 < 0$)
  $x(T)$ is the electricity consumption required for cooling ($\partial x/\partial T < 0$, $\partial^2 x/\partial T^2 \leq 0$)
  p is the electricity price in $/kWh
  - We assume $x(T)$ is a linear function of compressor run-time (Blonz et al., 2025)

→ The baseline setpoint $T^0 = \arg\max \{u(T) - px(T)\}$ is the cooling setpoint the household will have in a normal non-emergency hour, or during an energy emergency if they do not take conservation action.

Model of thermostat setpoint behavior

- **Second stage**: The thermostat setting is:

$$T = \begin{cases} T' \text{ if } Z > 0 \\ T^{default} \text{ otherwise} \end{cases}$$

where $T^{default}$ is the default thermostat setpoint and T' is the reoptimized thermostat setpoint that maximize:

$$U_2(T, p', s) = u(T) - p'x(T) - \mu(T, s)$$

$\mu(T, s)$ is the moral payoff component ($\partial\mu/\partial T > 0$, $\partial^2\mu/\partial T\partial s > 0$)

$\rightarrow$ Random variable Z determine which household take action, $Z = Z(\Delta U_2, \xi, s)$

- Increases with the cost of inaction ($\partial Z/\partial\Delta U_2 > 0, \partial Z/\partial s > 0$)
- Decreases with physical costs of adjusting/informational barriers ($\partial Z/\partial\xi < 0$)

Increasing price or moral cost improves welfare

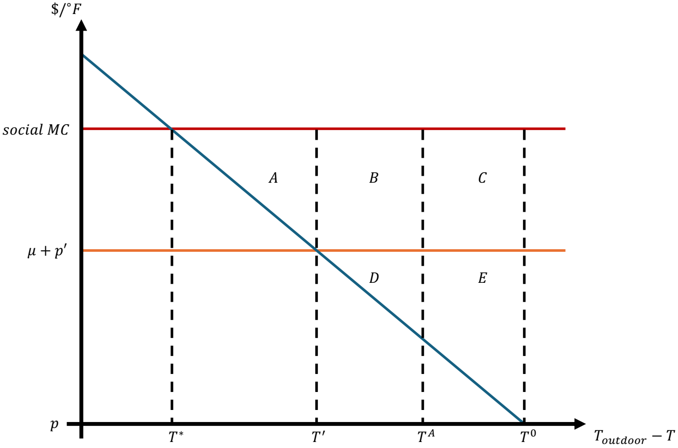
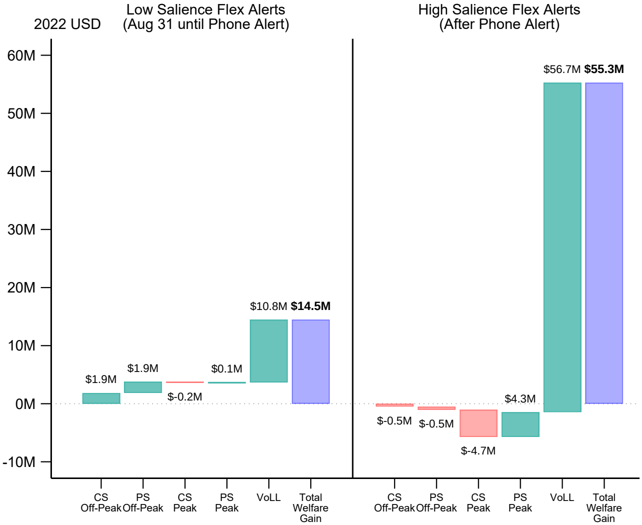


Figure 1: The marginal willingness to pay for cooling, with the baseline thermostat setpoint T^0, conservation thermostat setpoint T', and automation thermostat setpoint T^A.

Aggregate demand and welfare effect



- Our estimates translates to:
  Max. 800 MW reduction (low sal.)
  Max. 1,300 MW reduction (high sal.)

▸ Detail on aggregate demand calculation

- DRs only contributes ≈ 10%, due to low enrollment

- Flex Alerts (and DR) results in total welfare gain of $ 69.8M, primarily from the benefit of *avoided blackout*

▸ Theoretical framework for welfare analysis
▸ Elasticity estimates
▸ Daily welfare breakdown

Summary

- We study the California's Flex Alerts to estimate household response to voluntary conservation request and demand response:
  - → Salience plays a central role in voluntary conservation
  - → Automated DR consistently outperforms voluntary conservation
  - → Salience and automation interact in a complementary way
- We develop a framework to evaluate the welfare effect of emergency conservation requests:
  - → Demand reductions are substantial ($\approx$ 1,300 MW)
  - → Automated DR programs contributed less than 10 percent of the total reductions
  - → Primary value of emergency conservation is grid reliability in avoiding blackouts
- Our study offers insights into the design of effective conservation efforts in grid emergencies
  - → Incentives for pushing DR program enrollment and/or smart technology adoption
  - → Voluntary requests will continue if no DR program or supply-side improvement

Thank you!

Please reach out with comments/questions

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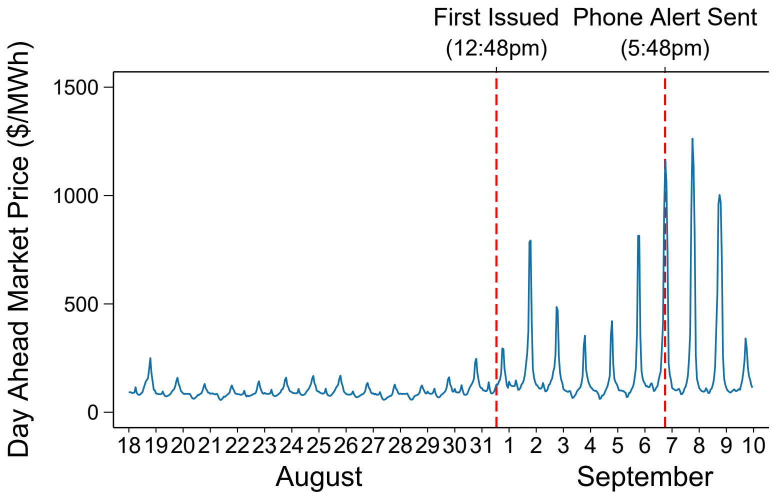
Back Up Slides

Power grid condition during September 2022 Flex Alerts



Extreme peak demands lead to scarcity in supply $\Rightarrow \uparrow$ wholesale electricity price, $\uparrow$ risk of blackout

Go Back

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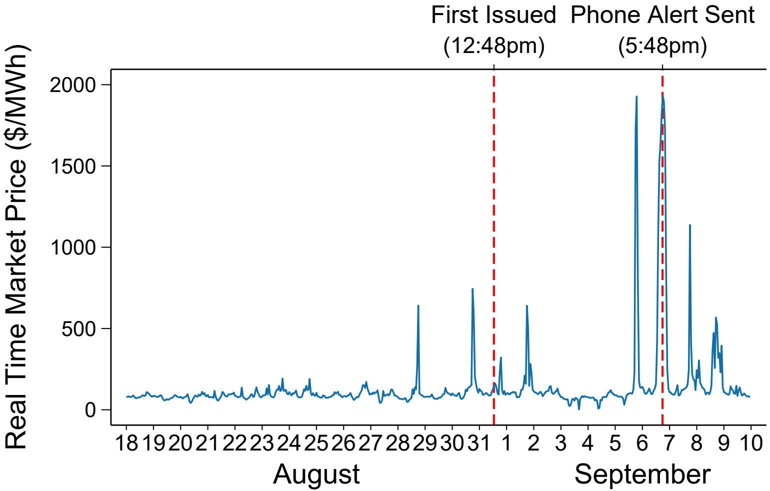

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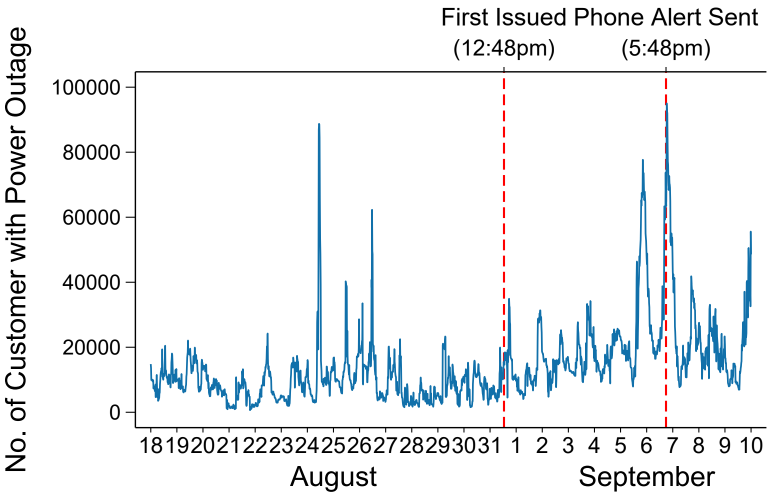

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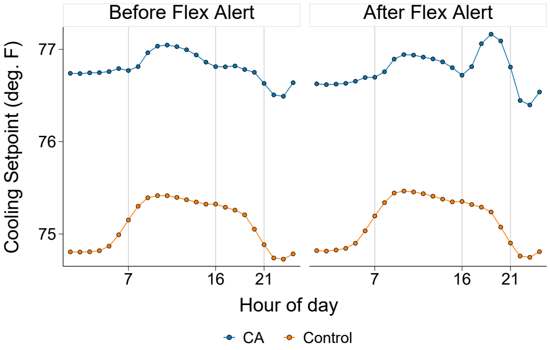
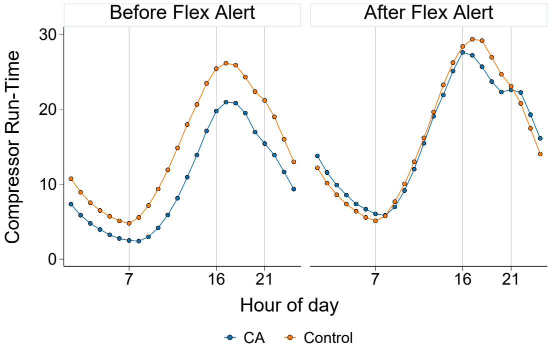
We observe cooling response during peak from the data



(a) Cooling Setpoint



(b) Compressor Run-Time

- Pre and post comparison for other variables
- Go Back

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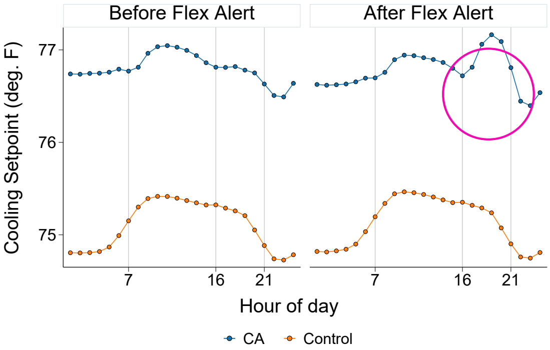

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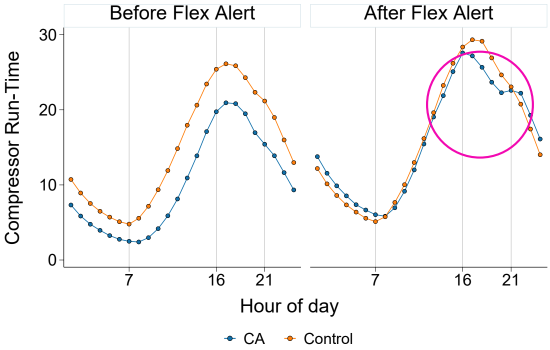

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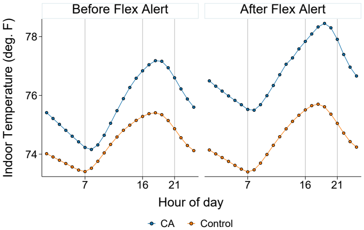
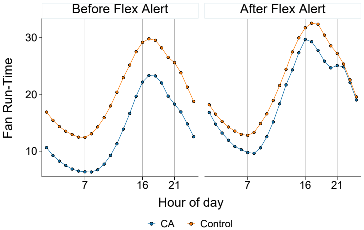
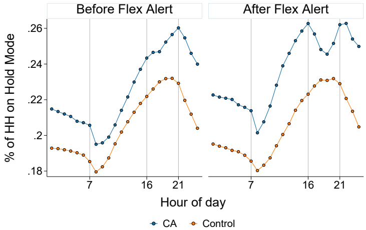


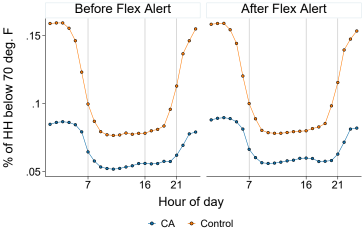
(a) Indoor Temperature



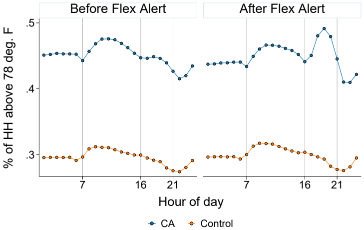
(b) Fan Run-Time



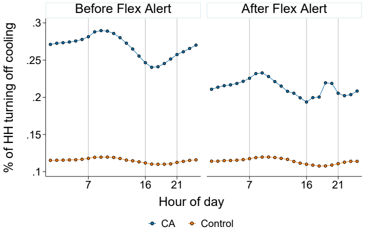
(c) Whether thermostat is on hold



(d) Whether setpoint $\leq$70°F



(e) Whether setpoint $\geq$78°F



(f) Whether cooling is off

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Detail on identifying DR households

Using the calendar event variable in the Ecobee data, I identified several demand response event names.

- I identify a general demand response event name that contains Demand Response (”DR”) and Precooling (”PC” or ”PRC”), which is a common term in AC load control.
- The second one is the California Public Utility Commission pilot Power Saver Rewards Program that started in May 2022. Participating customers receive a bill credit of $2 per kWh of electricity savings in a Flex Alert during my sample period. The program incurs no penalty for the household when they are enrolled and decide not to respond to emergency requests.
- I identify program names from SDGE, they are AC Saver DA (”ACSDA”), Bring Your Own Thermostat (”BYOT”), and Reduce Your Use (”RYU”).
- I also identify a demand response event name from Portland General Electric of which they collaborate with PGE.

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Detail on timing of Flex Alerts and DR events

Table 1: Summary of the Flex Alerts timing

Date	Start of peak	End of peak
Wednesday, August 31, 2022	4 p.m.	9 p.m.
Thursday, September 1, 2022	4 p.m.	9 p.m.
Friday, September 2, 2022	4 p.m.	9 p.m.
Saturday, September 3, 2022	4 p.m.	9 p.m.
Sunday, September 4, 2022	4 p.m.	9 p.m.
Monday, September 5, 2022	4 p.m.	10 p.m.
Tuesday, September 6, 2022	4 p.m.	9 p.m.
Wednesday, September 7, 2022	4 p.m.	9 p.m.
Thursday, September 8, 2022	3 p.m.	10 p.m.
Friday, September 9, 2022	4 p.m.	9 p.m.

Note. The information is compiled from CAISO's Grid Emergencies History Report.

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Detail on timing of Flex Alerts and DR events (cont.)

Table 2: Summary of the demand response event timing

Date	Start of event	End of event	DR treatment
Wednesday, August 31, 2022	7:25 p.m.	7:40 p.m.	7-8 p.m.
Thursday, September 1, 2022	5:00 p.m.	8:25 p.m.	5-9 p.m.
Monday, September 5, 2022	6:40 p.m.	8:20 p.m.	6-9 p.m.
Tuesday, September 6, 2022	4:10 p.m.	9:05 p.m.	4-9 p.m.
Wednesday, September 7, 2022	4:10 p.m.	8:55 p.m.	4-9 p.m.
Thursday, September 8, 2022	5:05 p.m.	8:15 p.m.	5-9 p.m.

Note. The information is compiled from CAISO's Today's Outlook. We define an hour to be demand response treatment when there is at least 15 minutes of demand response event within the hour.

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Detail on timing of Flex Alerts and DR events (cont.)

Table 3: Summary of the September 2022 Flex Alert events

Date	Time posted	Announcement
Wednesday, August 31, 2022	12:48 p.m.	Flex Alert issued
Wednesday, August 31, 2022	5:40 p.m.	Flex Alert extended
Thursday, September 1, 2022	4:23 p.m.	Flex Alert extended
Saturday, September 3, 2022	8:21 a.m.	Flex Alert issued
Saturday, September 3, 2022	4:03 p.m.	Flex Alert extended
Sunday, September 4, 2022	5:05 p.m.	Flex Alert extended
Monday, September 5, 2022	4:28 p.m.	Flex Alert extended
Tuesday, September 6, 2022	9:10 p.m.	Flex Alert extended
Wednesday, September 7, 2022	9:12 p.m.	Flex Alert extended
Thursday, September 8, 2022	10:00 p.m.	Flex Alert extended

Note. The announcement is summarized from the @flexalert Twitter account posts.

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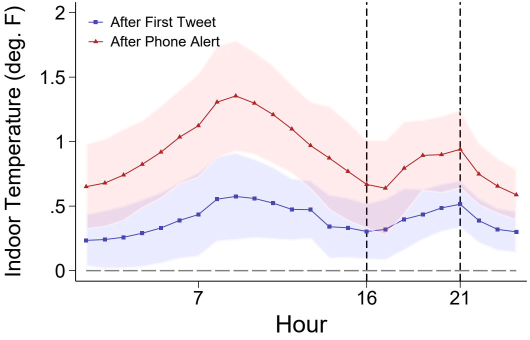
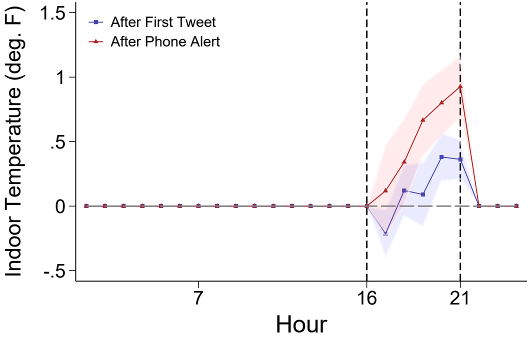
	(1) $\mathbb{1}$ (On Hold)	(2) $\mathbb{1}$ (Cool. Setpoint $\leq$ 70°)	(3) $\mathbb{1}$ (Cool. Setpoint $\geq$ 78°)	(4) $\mathbb{1}$ (Cooling Off)
After First Tweet				
Before-Peak	0.008***	0.002***	-0.009***	-0.036***
	(0.003)	(0.001)	(0.002)	(0.004)
Peak	0.005	0.001	0.007***	-0.024***
	(0.004)	(0.001)	(0.003)	(0.004)
Peak $\times \mathbb{1}$ (DR Event)	-0.015	-0.006***	0.033***	-0.020***
	(0.013)	(0.002)	(0.013)	(0.007)
After-Peak	0.003	0.001	-0.011***	-0.039***
	(0.002)	(0.001)	(0.003)	(0.004)
After Phone Alert				
Before-Peak	0.007*	-0.002	-0.006**	-0.045***
	(0.004)	(0.001)	(0.003)	(0.004)
Peak	-0.003	-0.003**	0.031***	-0.022***
	(0.009)	(0.002)	(0.006)	(0.004)
Peak $\times \mathbb{1}$ (DR Event)	-0.051***	-0.011***	0.107***	-0.026***
	(0.017)	(0.002)	(0.012)	(0.005)
After-Peak	0.000	-0.000	-0.003	-0.042***
	(0.005)	(0.001)	(0.004)	(0.006)
Pre-treatment Mean				
Before-Peak	0.21	0.08	0.41	0.23
Peak	0.25	0.07	0.39	0.20
After-Peak	0.24	0.10	0.38	0.22
No. of Household	12,135	12,135	12,135	12,135
Observations	6,632,642	6,632,642	6,632,642	6,632,642

▸ Go Back

Hourly effect of Flex Alerts and DR events (cont.)



(a) Effect of Flex Alerts



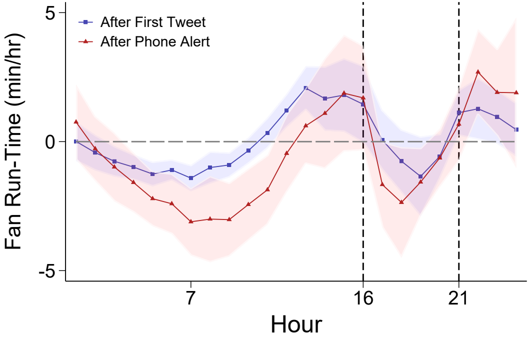
(b) Effect of DR events

Panel fixed effects: Hourly effect

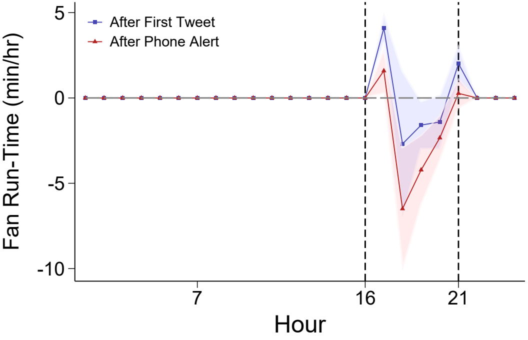
▸ Go Back

$$y_{ith} = \sum_{h=1}^{24} \beta_{FA,h} D_{ith} + \sum_{h=1}^{24} \delta_{FA,h} \left(D_{ith} \times \mathbb{1}[DRevent_{ith}] \right) + \sum_{h=1}^{24} \beta_{PA,h} P_{ith} + \sum_{h=1}^{24} \delta_{PA,h} \left(P_{ith} \times \mathbb{1}[DRevent_{ith}] \right)$$
$$+ \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}$$

Hourly effect of Flex Alerts and DR events (cont.)



(a) Effect of Flex Alerts



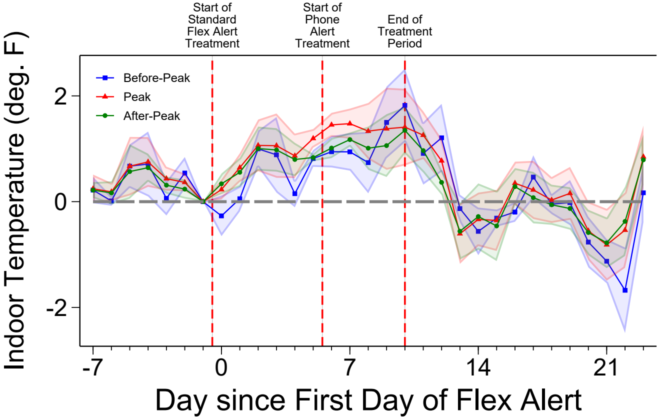
(b) Effect of DR events

Panel fixed effects: Hourly effect ▸ Go Back

$$y_{ith} = \sum_{h=1}^{24} \beta_{FA,h} D_{ith} + \sum_{h=1}^{24} \delta_{FA,h} \left(D_{ith} \times \mathbb{1}[DRevent_{ith}] \right) + \sum_{h=1}^{24} \beta_{PA,h} P_{ith} + \sum_{h=1}^{24} \delta_{PA,h} \left(P_{ith} \times \mathbb{1}[DRevent_{ith}] \right)$$

$$+ \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}$$

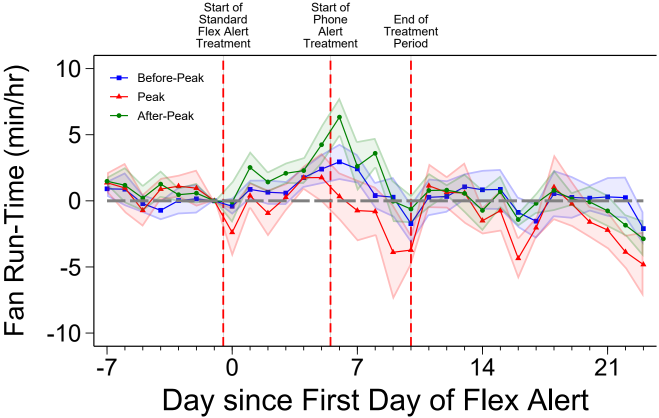
Event study on other outcomes



Panel fixed effects: Event study ▸ Go Back

$$y_{ith} = \sum_{t \in [-23,23], t \neq -1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t \in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

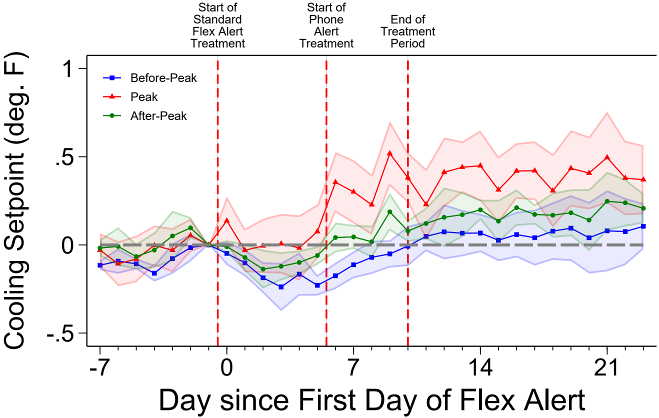
Event study on other outcomes



Panel fixed effects: Event study Go Back

$$y_{ith} = \sum_{t \in [-23,23], t \neq -1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t \in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

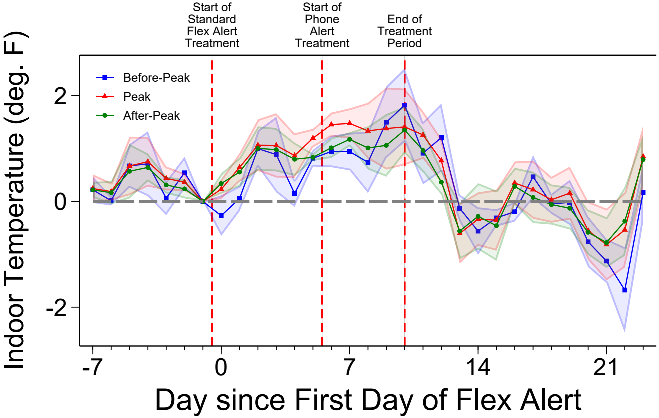
Event study using DD sample



Panel fixed effects: Event study Go Back

$$y_{ith} = \sum_{t \in [-7,23], t \neq -1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t \in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

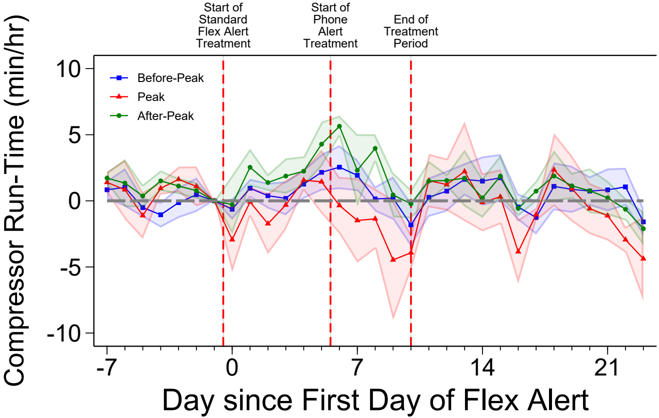
Event study using DD sample



Panel fixed effects: Event study Go Back

$$y_{ith} = \sum_{t\in[-7,23],t\neq-1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t\in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

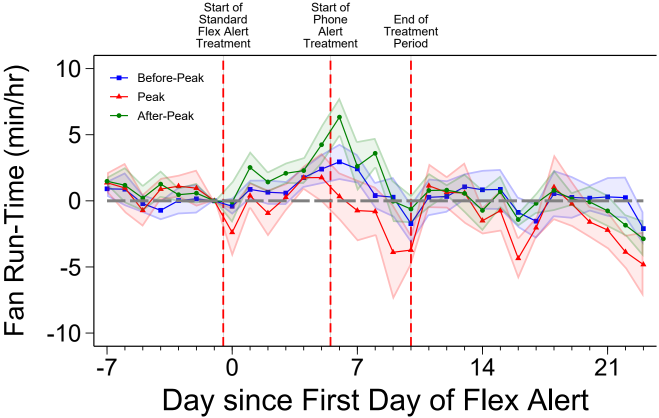
Event study using DD sample



Panel fixed effects: Event study ▸ Go Back

$$y_{ith} = \sum_{t \in [-7,23], t \neq -1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t \in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

Event study using DD sample



Panel fixed effects: Event study ▸ Go Back

$$y_{ith} = \sum_{t \in [-7,23], t \neq -1} \sum_{k=0}^{2} \beta_{tk} D_{itk} + \sum_{t \in DRevent} \delta_{tk} D_{it1} + \gamma X_{ith} + \alpha_{ith} + \varepsilon_{ith}.$$

Detail on aggregate demand

- We follow Blonz et al. (2021) to convert ATT on compressor run-time to electricity consumption reduction:

$$\Delta\text{Demand}_{ith}(\text{MW/HH}) = \hat{\beta}^{\kappa}_{ith}(\text{min/hr}) \times \frac{\text{UCR (BTU/hr.HH)}}{\text{SEER (BTU/W.hr)}} \times \frac{1 \text{ hour}}{60 \text{ min}} \times \frac{10^{-6}\text{ MW}}{\text{W}}$$

$$= \hat{\beta}^{\kappa}_{ith}(\text{min/hr}) \times 0.0000417(\text{MWh/HH.min}). \quad (1)$$

Since we do not observe households cooling systems characteristics, we assume

- Residential central air conditioner in the southern region following Appendix A of EIA Updated Buildings Sector Appliance and Equipment Costs and Efficiencies, with a Unit Capacity Ratio (UCR) of 36,000 BTU per hour per unit with a typical Seasonal Energy Efficiency Ratio (SEER) of 14.4 BTU per W per hour.

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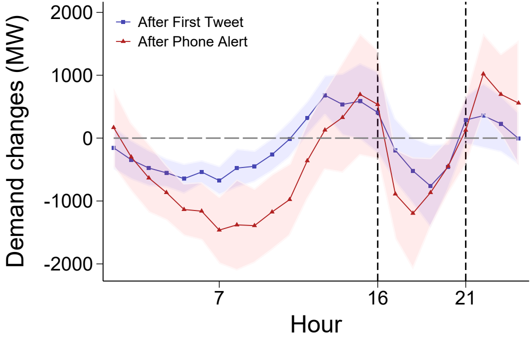
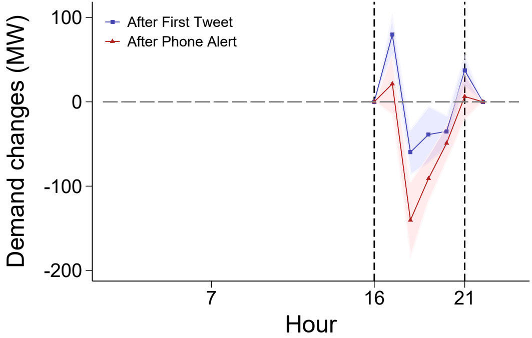
How big is the aggregate demand reduction?



(a) Aggregate Impact of Flex Alert, All households



(b) Aggregate Impact of DR Event, DR participant

- We convert the ATT and scale by # of household to calculate aggregate reduction
- This translates to max. reduction of 800 MW (low sal.) and 1,300 MW (high sal.)
- DRs only contributes $\approx$ 10%, due to low enrollment

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Detail on aggregate demand (cont.)

- To scale the individual number to aggregate, we assume
  - Total number of residential customers in CA: 13,550,586 households (ACS 1-year Estimates 2022) of which 72 percent of households in California own an AC following EIA (2020).
  - This leaves me with approximately 9.75 million households.
  - We assume 505,116 households to be demand response participants, and the rest are non-demand response households.

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Review: Welfare effect of Flex Alerts

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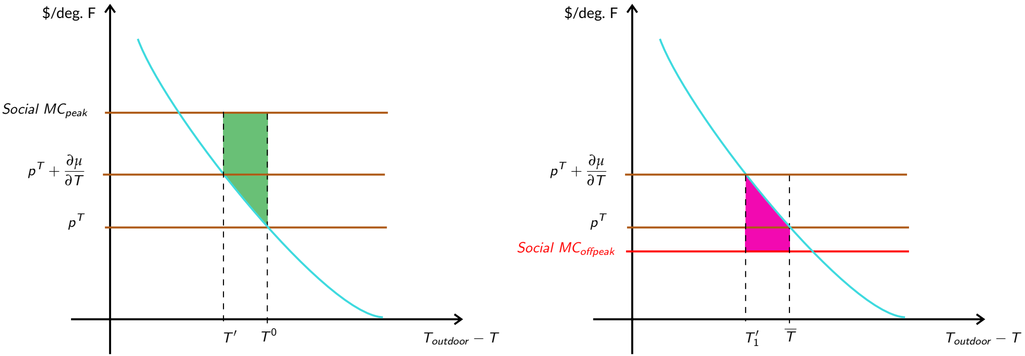

(a) Welfare gain from nudges

(b) Welfare losses from nudges

- Our estimates for pure moral suasion $\widehat{\beta^T} \rightarrow T'_1 - \overline{T}$
- Our estimates for demand response $\widehat{\delta^T}$ allow us to infer the price change $p^{T'}$ (for certain ε^T)

We simulate the welfare effect of Flex Alerts

1. Assume the demand for cooling for each i, t, h follow $T = \alpha^T + \beta^T D + \varepsilon^T \ln p^T$
2. Estimate $\widehat{\beta^T}$ and $\widehat{\delta^T}$ from empirical analysis
3. Resample i from California household and simulate welfare effect
   - 3.1 Draw the β^T and δ^T for each i, t, h from distribution of $\widehat{\beta^T}$ and $\widehat{\delta^T}$
   - 3.2 Estimate marginal effect of cooling setpoint on compressor run-time ($\partial\kappa/\partial T$)
   - 3.3 Compute cooling price, assuming baseline retail rate c$26/kWh (EIA, 2022)

$$p^T = -0.0417 p \partial\kappa/\partial T$$

   - 3.4 Compute semi elasticity, assuming elasticity (ε) of - 0.1 (Ito, Ida, and Tanaka, 2018; Ito, 2014; Wolak, 2011)

$$\varepsilon^T = \frac{\kappa}{\partial\kappa/\partial T}\varepsilon$$

▸ Elasticity estimates

   - 3.5 Compute changes in PS, CS, VoLL, and welfare
4. Compute aggregate welfare

Theoretical framework for the welfare analysis

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	Welfare Effects
Flex Alerts	
Change in Producer Surplus	$\Delta PS_{\text{Moral}} = \begin{cases} \beta^T(c^T - p^T) & \text{if } c^T \geq p^T, \\ -\beta^T(p^T - c^T) & \text{if } c^T < p^T. \end{cases}$
Change in Consumer Surplus	$\Delta CS_{\text{Moral}} = \begin{cases} -\frac{1}{2}(\beta^T)^2 \frac{p^T}{\varepsilon^T} & \text{if } \beta^T \geq 0, \\ \frac{1}{2}(\beta^T)^2 \frac{p^T}{\varepsilon^T} & \text{if } \beta^T < 0. \end{cases}$
Total Welfare Change	$\Delta W_{\text{Moral}} = \Delta PS_{\text{Moral}} + \Delta CS_{\text{Moral}}$
Demand Response Event	
Change in Producer Surplus	$\Delta PS_{\text{DR}} = \begin{cases} \delta^T(p^{T'} - p^T) & \text{if } p^{T'} \geq p^T, \\ -\delta^T(p^T - p^{T'}) & \text{if } p^{T'} < p^T. \end{cases}$
Change in Consumer Surplus	$\Delta CS_{\text{DR}} = \begin{cases} -\frac{1}{2}(\delta^T)^2 \frac{p^T}{\varepsilon^T} & \text{if } \delta^T \geq 0, \\ \frac{1}{2}(\delta^T)^2 \frac{p^T}{\varepsilon^T} & \text{if } \delta^T < 0. \end{cases}$
Total Welfare Change	$\Delta W_{\text{DR}} = \Delta PS_{\text{DR}} + \Delta CS_{\text{DR}}$
Value of Lost Load	
Gain from Avoided Outage in Peak Period	$\Delta \text{VoLL}_{Moral} = \beta^T \text{VoLL}^T$
	$\Delta \text{VoLL}_{DR} = \delta^T \text{VoLL}^T$

Cooling (semi)elasticity ranges from 0.2 to 0.59 °F

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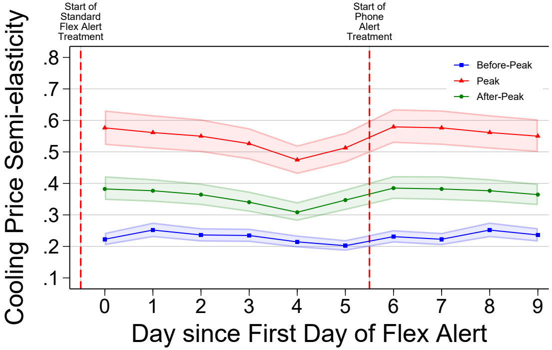
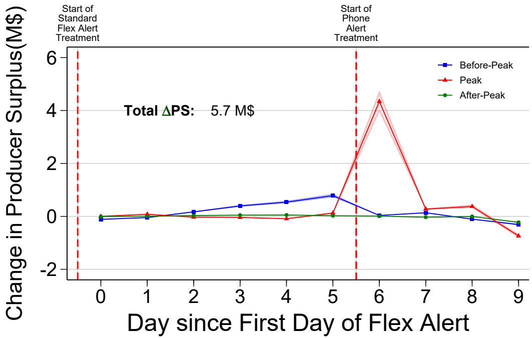


(a) Elasticity estimates during 2022 Flex Alerts

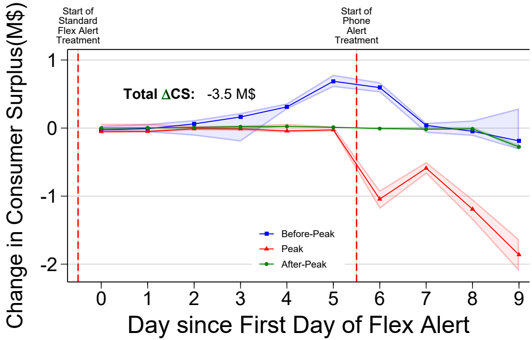
Our estimates are in the ballpark of values found in the literature

- Brewer (2023) find a 100% price increase reduce setpoint by 0.31 to 0.97 °F (winter)
- Fu, Novan, and Smith (2024) find a 100% price increase increase setpoint by 1.04°F (summer)

Daily breakdown of welfare effect



(a) Change in PS



(b) Change in CS

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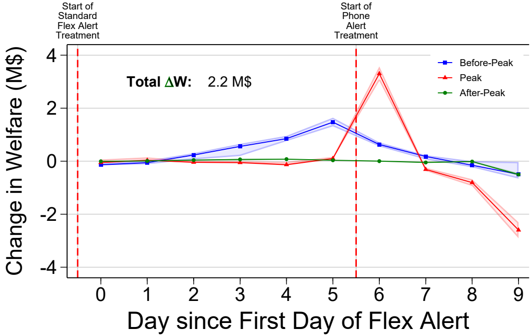
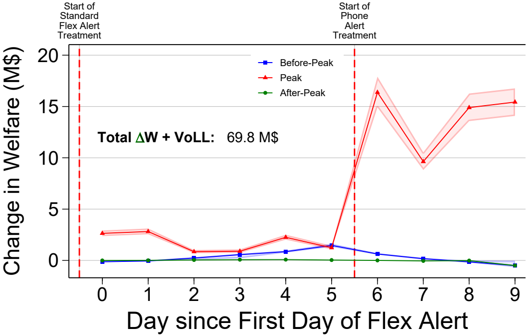
Daily breakdown of welfare effect



(a) Change in Welfare



(b) Change in Welfare + VoLL

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