Cooling demand during a heat wave: Household responses to extreme heat and to the government's call to save electricity

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ABSTRACT

During heat waves, air conditioning (AC) is the primary means of preventing heat-related health risks, including mortality. However, surges in cooling demand can disrupt the balance between electricity supply and demand, potentially causing large-scale blackouts. This study examines households' cooling demand during an extreme heat wave in California in September 2022. This 10-day event drove electricity demand to historic highs, bringing the state government close to implementing rotating outages and leading to an emergency alert to conserve electricity. We analyze this event using large-scale, high-frequency data from networked thermostats. The analysis investigates the sensitivity of AC usage to extremely high outdoor temperatures by regressing AC usage on temperature bins up to 110°F for over 10,000 households. The data show that cooling demand rises with temperature, even at extremely high temperatures that have not been examined in previous studies. The increase stems from greater air conditioner compressor operation in the absence of active human behaviors such as setpoint overriding. This suggests that overall AC system size is not a limiting factor for meeting AC load during heat waves. We also use the data to evaluate household responses to the government's request to save energy, which targeted hot, populated counties. To credibly compare targeted and untargeted households, we apply a matching difference-in-differences approach. The comparison indicates that AC usage is not responsive to the government's request, and the reduction in usage is minimal. Therefore, ACs controlled by networked thermostats alone cannot explain the system-wide drop after the government's emergency alert. These findings underscore the challenges of maintaining the balance between electricity supply and demand during more intense heat waves. These conclusions should be interpreted in light of the limitations of the study's data and identification strategy. In particular, the text-alert results pertain to households with networked thermostats and to the matched sample used for the comparison, which may limit generalizability.

Introduction

Climate change leads to heat waves across many regions of the world. Heat waves negatively impact society by increasing health risks, reducing agricultural yields, decreasing labor productivity, causing industry losses, and straining energy systems (Abunyewah et al. 2025). Mitigating these impacts requires affordable adaptation alongside costly mitigation strategies, such as the development of new low-carbon technologies (Carleton et al. 2022). A primary adaptation method is the use of air conditioning (AC). However, AC systems consume significant electricity, and demand surges during heat waves due to increased cooling needs. This drastic rise in electricity demand can disrupt the grid if supply is insufficient, creating stress on grid operations. This study examines the increase in cooling demand during heat waves and AC usage in response to grid operators' requests to conserve electricity.

Heatwaves are associated with substantial excess mortality worldwide. Zhao et al. (2024) estimate that heatwave-related excess deaths accounted for 0.94% of all deaths per warm season globally during 1990–2019. The IPCC reports that heat waves are expected to increase in frequency and intensity due to climate change (Calvin et al. 2023). Therefore, adaptation efforts are crucial. The use of AC systems is a prominent adaptation method, providing cool indoor environments to reduce heat-related mortality. As heat waves become more intense and frequent, AC usage will rise in both its adoption and operation (Davis and Gertler 2015).

As heat waves become more frequent and intense, cooling demand increases, even with strong energy efficiency measures. Balancing electricity supply and demand becomes more difficult during heat waves when cooling demand surges, overwhelming the grid and causing power outages. Faced with impending outages, grid operators have limited options to prevent blackouts, including monetary interventions such as dynamic electricity pricing (e.g., critical peak pricing and critical peak rebates) and non-monetary interventions like social norm feedback. However, dynamic pricing is often unpopular, with low take-up rates (Fowlie et al. 2021). When supply-side solutions are impractical, governments frequently resort to urgent appeals for electricity conservation (Meier et al. 2024).[1]

This study investigates household AC usage during the September 2022 heat wave in California. Total electricity demand in California reached a record high on September 6, and the California Independent System Operator (CAISO) struggled to meet supply with demand. The tightest balance occurred during peak demand hours, from 4 pm to 9 pm. To conserve electricity, CAISO issued a Flex Alert urging electricity consumers across its service area to conserve electricity voluntarily, and Energy Emergency Alerts to promote participation in energy markets and conservation. These measures were insufficient, prompting CAISO to prepare for rotating outages. Minutes before the outages began, the California Governor's Office of Emergency Services (CalOES) texted 27 million mobile phones in California, asking residents in hot and populated counties to reduce unnecessary electricity use "to protect public health and safety." Total demand fell immediately, and the grid was balanced without implementing rotating outages. No institution has comprehensively evaluated the exceptional reduction in demand. It remains unclear which sectors—residential, commercial, industrial, or transport—were responsible or what measures were implemented. This limited understanding impedes grid operators' ability to prepare for future, more intense heat waves. It is generally assumed that the savings originated in the residential sector through AC use as CalOES targeted with high AC usage (CalOES 2022). This grid crisis in California raises two questions: (1) Will cooling demand increase further during more intense heat waves? (2) What drove the reduction in cooling demand after CalOES's text alert?

Previous studies on energy usage during extreme temperatures and grid crisis

Previous research shows that electricity consumption increases as outdoor temperature rises. Our study differs in two ways. First, most prior studies use total electricity consumption (De Cian et al. 2025; Manderson and Considine 2025), while we utilize high-frequency data from networked thermostats. These thermostats regulate residential heating, ventilation, and air conditioning

[1] Although this study focuses on heat waves, cold waves can also trigger power outages, especially when they coincide with supply-side shortages. Such an event occurred in Japan in late March 2022, Texas and Oklahoma in February 2021, France in 2022 and 2023, and Alberta in January 2024 (Meier et al.,2024).

(HVAC) systems by activating cooling when indoor temperatures exceed user-defined setpoints. Networked thermostats typically record HVAC runtime, temperature setpoints, and user overrides of preset schedules. HVAC runtime serves as an excellent proxy for the energy use of single-speed HVAC systems.[2] These data are reported every five minutes. Thermostat data enable researchers to study cooling demand exclusively. Second, previous studies typically consider temperatures up to 90°F. Particularly, Ge and Ho (2019) and Huchuk et al. (2018) use networked thermostat data to analyze how extreme temperatures affect cooling and heating demand, with an upper limit of around 90°F. Our study examines the extreme heat wave in California to assess AC sensitivity to outdoor temperatures up to 110°F. Expanding the temperature domain is critical for predicting the impacts of future, more intense heat waves (Calvin et al. 2023). Specifically, our estimates of AC temperature sensitivity indicate that cooling demand may continue to rise as temperatures increase, likely because cooling systems are oversized rather than due to changes in human behavior. This finding connects our study to the engineering literature on optimal HVAC system sizing. Oversizing has long been recognized as a source of inefficiency (Reddy and Claridge 1993), and more recent work continues to document the importance of proper sizing for energy use and peak demand (Djunaedy et al. 2011; Chiu and Krarti 2021).

Another strand of related literature evaluates non-monetary policy interventions to conserve electricity during peak demand hours. Economists have investigated how these interventions contribute to electricity conservation during peak demand. These studies often apply field experiments to ensure internal validity. Few studies have used non-experimental data to examine the effects of government calls to save electricity empirically, thereby helping generalize findings from field experiments to ensure external validity. Reiss and White (2008) and Costa and Gerard (2021) measure the combined effects of monetary and non-monetary policy interventions on residential electricity consumption. Agarwal, Sing, and Sultana (2022) investigate a public media campaign in Singapore to save electricity that did not specifically target peak power. This study's policy intervention differs from prior empirical studies in two ways. First, the text message from CalOES is a non-monetary intervention aimed at reducing electricity demand during historically critical peak hours. Second, it is highly intrusive and delivered directly to individuals rather than through mass media. This study closely parallels an investigation by Brewer and Crozier (2025), which used networked thermostat data to assess natural gas savings after the governor of Michigan urged consumers to conserve during a temporary gas shortage. Our study differs from Brewer and Crozier (2025) in that we focus on California's summer electricity crisis and investigate how cooling demand responds to the non-monetary policy intervention.

Details of the California 2022 heat wave

In the summer of 2022, a 10-day heat wave struck California from August 31 to September 9. Daily maximum temperature in large parts of California exceeded 100°F during this period, about 10°F above the previous year's level. Figure 1 plots daily maximum temperatures in

[2] Most heating and cooling systems in North America have only one speed; therefore, the number of operating minutes per hour is a good proxy for electricity or natural gas consumption. The runtime metric is not appropriate for variable-speed units, which are common in other parts of the world (and only recently being introduced in the United States). In addition, the Ecobee thermostat is not natively compatible with variable-speed units, treating them as single-speed units.

Sacramento from August 23 to September 9 for 2022 alongside those from the same period in the preceding four years. The figure clearly shows that the 10-day period from August 31 to September 9 was exceptionally hot in 2022, resulting in almost 400 deaths (Milet et al. 2023).

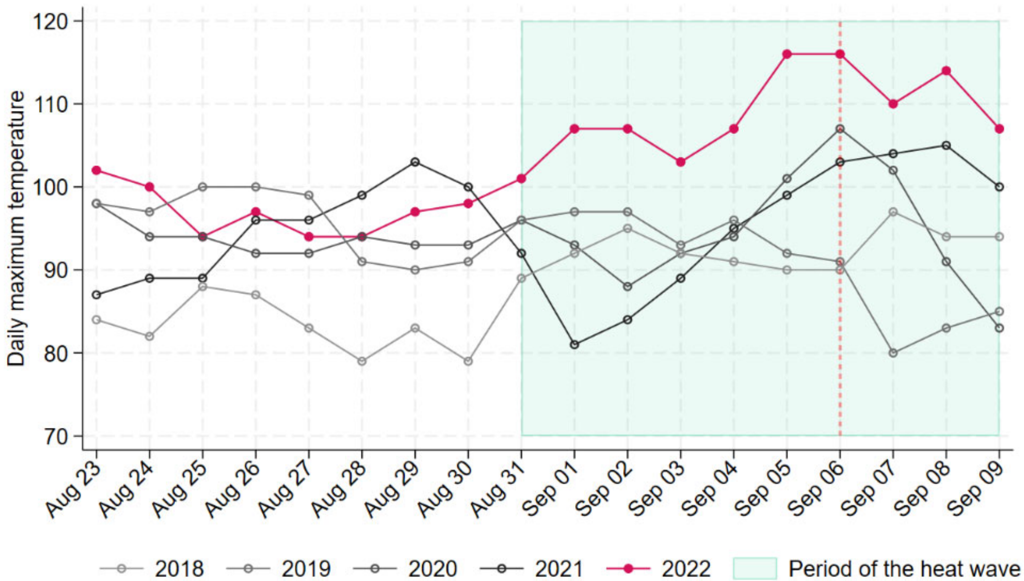


Figure 1. Maximum outdoor temperature in Sacramento during the heat wave period. The temperature data was retrieved from NOAA Climate Data Online. *Source*: NOAA (2025).

The heat wave led CAISO to a record-high electricity load. Figure 2 shows the average electricity demand over the 10 days in 2022 compared with the preceding 4 years, indicating that demand in 2022 was significantly higher. From the first day of the heat wave, August 31, CAISO issued a Flex Alert, a state-wide voluntary program initiated after the 2000 electricity crisis to stimulate peak power savings. Consumers who signed up for the Flex Alert receive notifications encouraging actions such as pre-cooling to save electricity. On the peak-demand day, September 6, electricity demand exceeded 50 GW, as shown in Figure 2. Despite of the Flex Alert, demand did not decrease significantly. At 5:17 pm, CAISO alerted utilities to prepare for rolling outages.

At 5:45 pm on September 6, CalOES sent an emergency text message to California residents, requesting reductions in non-essential electricity use. The message sent to residents is as follows (CalOES 2022): “Conserve energy now to protect public health and safety. Extreme heat is straining the state energy grid. Power interruptions may occur unless you take action. Turn off or reduce nonessential power if health allows, now until 9 pm.” This messaging system was designed to inform Californians about natural disasters and abducted children. This marked the first statewide use of a notification system in response to an electricity crisis. The message reached 27 of the 58 counties, covering approximately 27 million of the 32 million telephones registered in California. CalOES targeted counties with high temperatures and population density, anticipating high cooling demand.

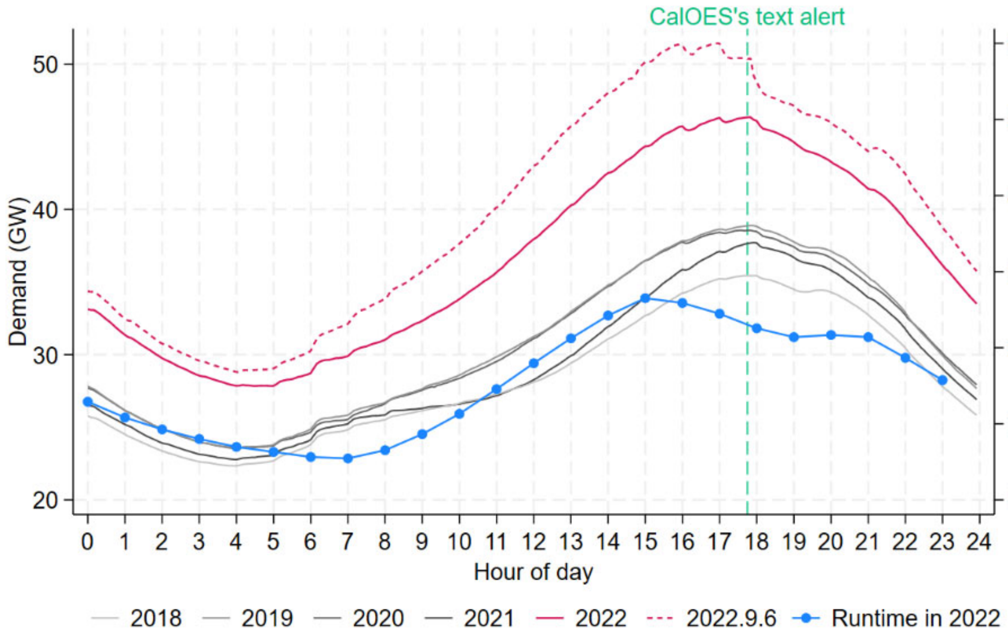


Figure 2. 10-day average electricity demand and AC runtime. The system demand data was retrieved from CAISO Today's Outlook. *Source*: CAISO (2025).

One hour after the text message, electricity demand fell by almost 1.1 GWh (2.2%) relative to the hour-ahead forecast (Figure 2). The text message seemingly reduced peak demand, and CAISO did not initiate any rotating outages. However, little is known about the sources of demand reductions. CAISO and other authorities did not investigate which customers responded to the text alert or the measures they took. It remains unclear whether the savings came from the residential, commercial, or industrial sectors.

Residential air conditioners can significantly reduce peak demand for three reasons. First, the residential sector accounted for approximately 35% of total annual electricity consumption in California in 2021 (CEC 2025c), and this fraction likely increases during summer peak-demand hours because of cooling demand. In addition, AC is the most significant end-use electricity consumption in the United States (EIA 2023). Figure 2 further shows that average peak AC runtime in our sample of 11,714 networked thermostats (see next section) closely aligns with CAISO's total demand, suggesting that residential cooling demand makes up a substantial portion of system demand during summer peak hours. Second, households can reduce electricity use by adjusting thermostat settings. Burkhardt, Gillingham, and Kopalle (2023) empirically show that AC is the largest contributor to the response to critical peak pricing among major appliances, and Brewer and Crozier (2025) find that households adjust thermostat settings in response to the government's call to reduce heating demand. Combining these facts and findings, adjustments to thermostats could contribute significantly to the reduction.

Thermostat, household attributes, and geographical data

The primary data on networked thermostats was provided by Ecobee, a manufacturer operating mainly in North America, through its "Donate Your Data" (DYD) program. The data consists of households that have installed an Ecobee thermostat and have agreed to share their data with researchers by voluntary participation in the DYD program.[3] For AC usage, we observe compressor runtime, temperature setpoints, operating modes, and programmed events every 5 minutes. Households can adjust the AC by directly controlling the thermostat or remotely via a mobile app. AC usage is linked to self-reported household attributes, including city name, building type, total floor area, building age, and number of occupants. As of January 2026, the dataset includes over 23,000 thermostats in California.

From the original five-minute AC usage data, we constructed hourly data with three primary outcome variables. The first variable is the cumulative runtime, in minutes per hour, of the first stage of compressor cooling systems. For the single-speed system, runtime serves as a proxy for household cooling demand and electricity use. Thus, we can investigate household cooling demand during a heat wave by analyzing compressor runtime. The second variable is the average thermostat setpoint at a given hour, which helps us understand how occupants respond to outdoor temperature and alerts. For instance, if occupants feel too hot at a given setpoint, they lower it to cool the indoor environment, increasing the air conditioner's runtime and electricity consumption. The third variable measures how often a household overrides its thermostat setpoint within an hour. The original five-minute data records when households override pre-set temperature settings every five minutes, with overridden setpoints in effect until either several hours (typically two or four hours) pass or the next pre-set schedule begins. Therefore, the duration of an override usually lasts several hours. We define a household's first interaction with its thermostat as the five-minute window during which consecutive overriding durations initiate. We then count the number of first interactions in an hour to determine the overriding frequency.[4] For example, an overriding frequency of 2 means occupants override their thermostats at least twice within an hour. This frequency indicates how often households interact with their thermostats. We expect this variable to increase if occupants feel uncomfortable due to a heat wave or respond to government warnings by adjusting thermostat setpoints.

In addition to the primary outcome variables, we constructed two additional variables from the thermostat data. The first variable indicates whether the ACs operated at full capacity, defined as running continuously for 60 minutes within an hour. We use this variable in the AC temperature sensitivity analysis to assess whether AC usage saturates as outdoor temperatures rise. The second variable measures the minutes within an hour during which the cooling runtime is zero. The original data include the runtime, in minutes, of the second-stage compressor cooling systems. We derived the turn-off minutes variable by calculating the number of minutes in an hour during which neither the first nor the second stages are used. This variable is used for the text-alert analysis, as CalOES requested that households turn off nonessential electricity.

The evaluation of text alert impact requires the location (e.g., county) of the installed thermostat. Only households in targeted counties received a text alert from CalOES. Participants in the DYD report only the city, which we match to a county. Approximately 99% of the locations were successfully matched with a county.

For all households in the thermostat dataset, we utilize the reported city name to supplement three pieces of geographical information from non-thermostat sources. First, we collected hourly

[3] Households in the Ecobee dataset are self-selected, which may raise concerns about selection bias. However, Meier et al (2019) show that observable characteristics of Ecobee households are broadly similar to those of a representative sample of U.S. households. Although the Ecobee sample includes a higher share of single-person households, other characteristics, such as geographic distribution, age composition, and household size, closely match those of the general population.

[4] If households override their thermostats in two consecutive five-minute windows, the second interaction is not counted by construction. Therefore, this variable provides a lower bound on the actual frequency of overrides.

outdoor temperature data from Open-Meteo by matching the city name with a nearby weather station (Open-Meteo 2025). We use the hourly temperature data as the primary regressor in the AC temperature-sensitivity analysis and as a control variable in the text-alert analysis. The second information is the climate zone classification published by the CEC (CEC 2025b). The entire state of California is divided into 16 different climate zones. We use this climate zone classification to control for cooling demand. Finally, the territory map of the Investor-Owned Utilities and Publicly-Owned Utilities published by CEC (CEC 2025a) is used to control for utility-specific programs such as demand response events and time-of-use (TOU) tariffs.

Table 1 reports descriptive statistics of the outcome variables and outdoor temperature in our sample. The study sample consists of 11,714 households with a balanced panel data, spanning from August 23 to September 9. The first two columns summarize households used for AC temperature sensitivity analysis. Columns (1) and (2) present summary statistics before and during the heat wave, respectively. The table indicates that AC usage increases during the heat wave. For example, runtime increases by over 6 minutes per hour, and the share of households with AC running at full capacity rises by 5 percentage points. The average outdoor temperature during the heat wave is 9°F higher than that of the week prior.

Table 1. Descriptive statistics of outcome variables

	AC temperature sensitivity analysis		Text alert analysis	
	Before heat wave	During heat wave	Targeted	Untargeted
	(1)	(2)	(3)	(4)
Runtime (minute)	9.33 (15.7)	15.3 (19.6)	13.3 (18.5)	5.05 (13.4)
Setpoint (°F)	76.7 (4.73)	76.7 (4.71)	76.7 (4.65)	76.5 (5.55)
Overriding frequency	0.0145 (0.123)	0.0200 (0.144)	0.0178 (0.136)	0.00808 (0.0916)
Full capacity	0.0279 (0.165)	0.0722 (0.259)		
Turn-off minutes			38.7 (23.4)	48.0 (21.8)
Outdoor temperature (°F)	73.7 (11.6)	82.8 (13.2)	79.4 (13.1)	69.1 (14.0)
Number of obs.	2,608,128	3,260,160	4,818,660	411,180
Sample period	2022.8.23-8.30	2022.8.31-9.9	2022.8.23-9.7	

The standard deviation is in parentheses.

Columns (3) and (4) summarize variables for households used in the text-alert analysis; Column (3) corresponds to households in the targeted counties, while Column (4) pertains to untargeted counties. This analysis excludes observations from the 48 hours post-text alert, focusing instead on the effects of the text alert on AC usage during peak-demand hours on the event day and following day. The number of observations in treated counties far exceeds that in untargeted counties, as expected, because CalOES targets populated counties. Differences in variables between Columns (3) and (4) align with CalOES's strategy to target hot counties. For instance, the average runtime in targeted counties exceeds that in untargeted counties by over five minutes per hour. Additionally, the average outdoor temperature in targeted counties is 7°F higher than in untargeted counties. To credibly compare targeted and untargeted households, we address these systematic differences using a matching method.

Method

Responses to outdoor temperature

We exploit the exogenous variations in outdoor temperature to identify AC sensitivity to outdoor temperatures. We regress AC usage on outdoor temperatures, controlling for a series of fixed effects. Empirically, we estimate the following regression equation:

$$Y_{imdh} = \sum_{b \in B} \beta_b T^b_{imdh} + \delta_{mdh} + \alpha_{iw(m,d)h} + \varepsilon_{imdh}, \tag{1}$$

where Y_{imdh} represents one of the four outcome variables listed in Table 1 (i.e., runtime, setpoint, overriding, and full capacity) for household i at hour h on day d in month m. T^b_{imdh} is the variable of our interest and represents the bth temperature bin. The temperature bins b are defined as larger than 110°F, less than 60°F, and the ten bins with a size of 5°F in between. The flexible control for outdoor temperature allows us to estimate a nonlinear relationship between AC usage and outdoor temperatures, β_b.

Two fixed effects are included in the regression equation. The first one is time fixed effects (δ_{mdh}) that capture any time-specific effects that are common across California. The inclusion of time fixed effects is particularly important in our context to control for the impact of Flex Alerts issued by CAISO. Flex Alerts are issued across the state without targeting strategies. Therefore, δ_{mdh} is expected to absorb the effects of Flex Alerts, if any, on AC usage. The second one is household-by-week-of-day-by-hour fixed effects. They would capture any household-level weekly and hourly variations, such as household occupancy and TOU tariffs. The last term in Equation (1) is the idiosyncratic shocks.

Responses to the text alert

Our strategy to identify the text alert's effects is to apply the difference-in-differences (DiD) method, comparing the targeted and untargeted counties before and after the text alert. Specifically, we estimate dynamic effects to determine when household behavioral changes occurred. We estimate the following two-way fixed effects model:

$$Y_{it} = \sum_{j=-336}^{-2} \beta_j^{before} \mathbf{1}\left[t = g + j\right] \cdot D_i + \sum_{j=0}^{48} \beta_j^{after} \mathbf{1}\left[t = g + j\right] \cdot D_i + \delta_t + \alpha_i + \varepsilon_{it}, \tag{2}$$

where $\mathbf{1}[\cdot]$ is an indicator function equal to one if the condition inside the brackets is satisfied and zero otherwise, and g is the time when CalOES sent a text message (i.e., 5:45 pm on September 6). We estimate dynamic effects for two weeks (336 hours) before and 48 hours after the text alert. In this model, we also include utility-by-week-of-day-by-hour fixed effects to control for utility-specific demand response programs and TOU tariffs.

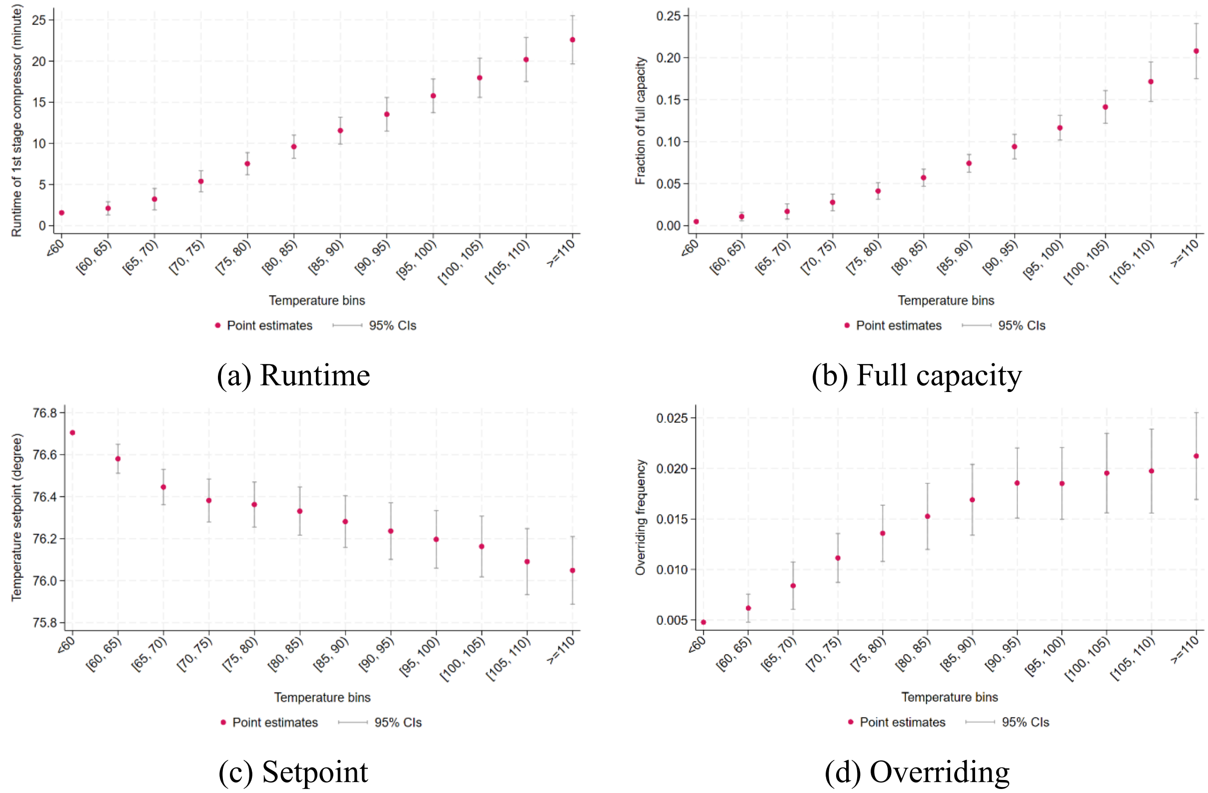
Comparing targeted and untargeted counties may lead to biased estimators. CalOES targeted hot and populated counties, and, as shown in Table 1, AC usage in the targeted counties differs systematically from that in the untargeted counties. The DiD method requires a parallel trends assumption, which holds if AC usage in the targeted and untargeted counties would have trended similarly in the absence of the text alert. The systematic difference can violate this key assumption. We apply a matching method to adjust for systematic differences. After matching the thermostats with relevant covariates, the text alert can be considered exogenous for several reasons. First, CalOES's targeting strategy operates at the county level, not at the individual household level, making it unlikely that individual household AC usage influences it. Second, the list of targeted counties was prepared in advance and not based on real-time AC usage, further indicating that AC usage in our sample is unlikely to affect CalOES's targeting strategy. Third, the targeting strategy relies on average temperature, population density, and cooling demand. Controlling for these variables allows us to eliminate differences between targeted and untargeted counties. Thus, a matching DiD can credibly identify the causal effects of CalOES's text alert on AC usage.

The matching method we applied is the Coarsened Exact Matching (CEM) method (Iacus, King, Porro 2012). We first coarsen pre-treatment covariates to create blocks with similar characteristics, then match households in the untargeted counties to those in the targeted counties within the same block. The CEM method produces household weights based on their frequency within a block, which are used to estimate Equation (2). Matching variables capture two factors influencing CalOES's targeting strategy: climate and population. To control for climate, we constructed three variables from pre-treatment data: (1) daily average outdoor temperature, (2) the difference between daily average maximum and minimum temperatures (capturing intra-day temperature variations), and (3) the climate zone classification developed by CEC. To control for population, we used the total floor area of houses reported by households in the sample, assuming a negative correlation between population and house size. In total, four matching variables are used to balance households in targeted and untargeted counties. Our matching strategy retains 944 households in targeted counties and 432 in untargeted counties; however, most households in targeted counties are excluded from the text alert analysis because their cooling demand does not align with that in untargeted counties under CalOES's targeting strategy.

Results

AC sensitivity to outdoor temperature

Figure 4 summarizes the estimation results of the AC sensitivity to outdoor temperature based on Equation (1). The estimated responses are relative to the response to the outdoor temperatures below 60°F. Figure 4(a) shows that air conditioner runtime increases with outdoor temperatures, with no clear evidence of saturation. Compared to hours when the outdoor temperature is below 60°F, runtime increases by 15 minutes at 90–95°F and by 23 minutes at 110°F or higher. Figure 4(b) indicates that the fraction of AC units running at capacity follows a similar trend. The fraction is nearly zero below 60°F, indicating minimal AC use for 60 minutes per hour. However, it keeps increasing with outdoor temperatures, exceeding 20% at 110°F or higher.



(a) Runtime

(b) Full capacity

(c) Setpoint

(d) Overriding

Figure 4. Estimates of AC sensitivity to outdoor temperatures.

By contrast, Figures 4(c) and 4(d) show that responses of setpoints and overriding frequency to outdoor temperatures are not drastic. As outdoor temperatures exceed 60°F, setpoints decrease to cool indoor environments, indicating that households adjust thermostat setpoints in response to rising temperatures. However, setpoints do not continue to decline: the effects of outdoor temperature on setpoints are statistically indistinguishable for temperature bins equal to or greater than 90°F. Similarly, the frequency of overrides increases with outdoor temperatures above 60°F, but the effects are statistically indistinguishable at moderately high outdoor temperatures.

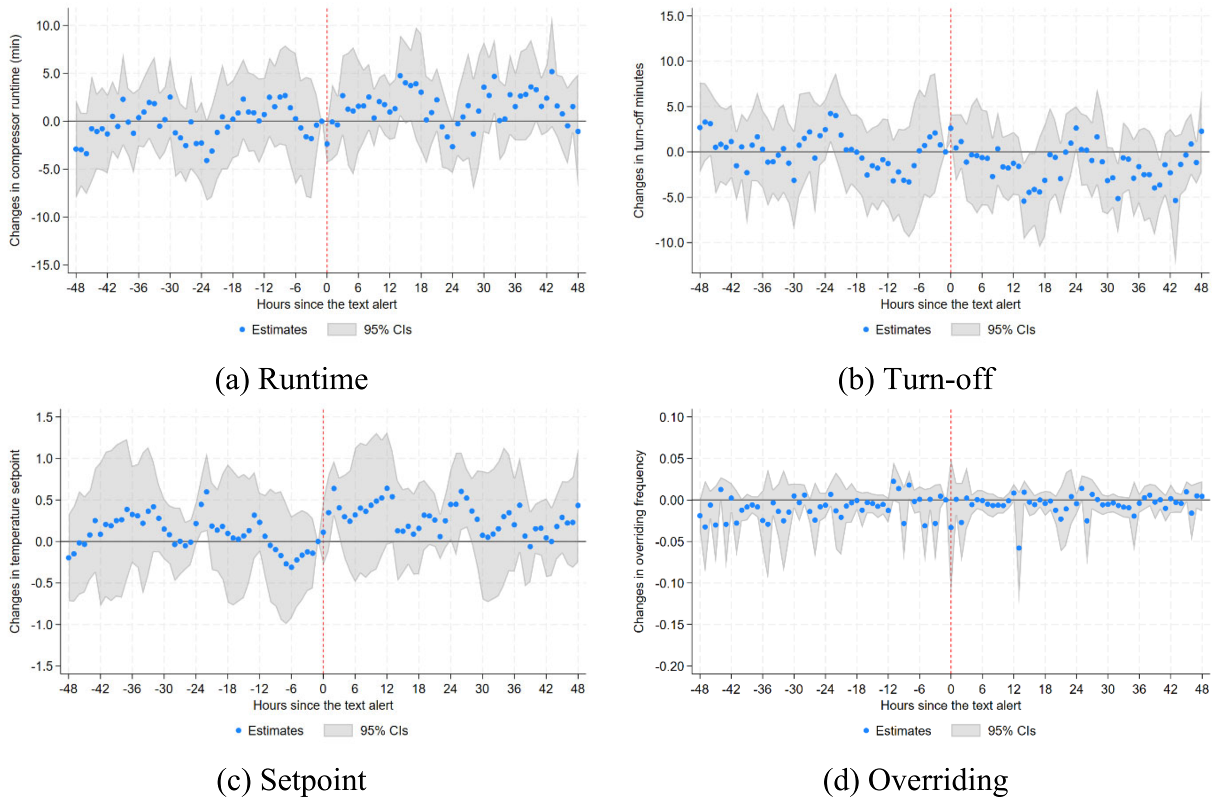
Our results suggest that, while human behavior becomes less responsive to rising outdoor temperatures, electricity consumption from AC units continues to increase. As shown in Figure 4, setpoints and overriding frequency are responsive at lower outdoor temperatures (less than 70°F), but become unresponsive at higher temperatures. These results indicate that households adjust thermostat settings by overriding preset schedules when outdoor temperatures rise from low levels, but do not actively change thermostat settings at high outdoor temperatures. However, Figures 4(a) and 4(b) illustrate that electricity consumption does not reach saturation. AC units consume electricity to cool when indoor temperatures exceed the setpoint. Increased AC usage at higher temperatures stems from rising indoor temperatures as outdoor temperatures climb, enlarging the gap between the setpoint and indoor temperatures. Thus, higher electricity consumption at elevated temperatures is driven more by AC's embedded features than by household interactions with their thermostats. AC usage will continue to rise until reaching the limit of the air conditioner's capacity. Beyond this limit, indoor temperatures will continue to rise because the AC cannot fully cool the home to the desired temperature, promoting occupants to interact more with their thermostats. We did not observe this phenomenon, suggesting that most residential air conditioners have excess capacity. Increased AC usage in high-temperature bins is also likely lower AC efficiency, as systems generally consume more electricity as outdoor temperatures rise. Additionally, households may have responded behaviorally to extreme temperatures by, for example, leaving home for cooler places.

The results indicate that residential AC system capacity did not limit electricity consumption during the September 2022 heat wave. While this supports AC as an effective mitigation measure up to a point, it is a strong contributor to grid instability. In our analysis, the largest closed bin of outdoor temperature is [105, 110) due to the variation in our sample. Figure 4(b) shows that 20% of ACs operate at full capacity when the outdoor temperature falls within this bin. Most ACs did not operate at full capacity during the 2022 California heat wave. If outdoor temperatures exceed those in this study, the proportion of ACs running at full capacity and the average runtime will likely increase. Consequently, grid operators may face greater challenges in balancing electricity demand and supply during future, more intense heat waves.

Effects of the text alert on air conditioning usage

Figure 5 presents the estimated coefficients from Equation (2), which measure the dynamic causal effects of the text alert relative to baseline AC usage one hour prior. The figure shows the estimates 48 hours before and after the text alert. Overall, consistent with the average effects reported in Table 2, the text alert had limited effects. A significant decrease in runtime and a notable increase in other variables would have been expected immediately after the alert if it had significantly affected AC usage. However, responses to the text alert were minimal. For instance, Figure 5(a) shows that the decrease in runtime after one hour is statistically significant at conventional levels. However, the reduction is only 2.4 minutes per hour and is not substantially larger than the runtime variation during the pre-event periods. Furthermore, this reduction disappears two hours after the text alert. The effects on turn-off behavior exhibit a similar pattern, as shown in Figure5(b). The text alert slightly encouraged households to turn off their air conditioners, but the effect was small and short-lived.

The limited effects of the text alert on AC usage are supported by its dynamic impacts on thermostat setpoint and households' overriding behavior. Both coefficients show no statistically significant effects within one hour after the text alert. While a slight increase in setpoints occurs several hours post-alert, these estimates are comparable to pre-alert variations. Additionally, no effects on overriding behavior are observed within 48 hours after the text alert. These results indicate that, after receiving the text alert, the average household did not adjust its networked thermostats by overriding setpoints. Instead, they may have temporarily turned off their thermostats, then turned them back on after an hour. However, such behavior is limited, as the estimated coefficients do not differ significantly from the pre-alert coefficients. These limited thermostat-level responses imply that the large system-wide demand decline observed after the CalOES alert (Figure 2) cannot be explained solely by networked residential AC.



(a) Runtime (b) Turn-off

(c) Setpoint (d) Overriding

Figure 5. Estimates of dynamic effects of CalOES's text alert

Discussion

Our study shows that ACs operate more often as outdoor temperatures rise, regardless of occupants' behavior. One would expect this increase to continue until the equipment's capacity limit is reached. Beyond that, indoor temperatures are expected to rise, as the AC can no longer fully cool the home to the desired temperature. We did not observe saturation in AC usage, suggesting most residential ACs maintain sufficient capacity.

The minimal effects of CalOES's text alert indicate that most of the subsequent reduction was driven by appliances other than ACs controlled by networked thermostats. Possible sources include substantial loads such as ACs with non-networked thermostats, lighting, and EV charging. Further research is necessary to identify the significant factors influencing the effects of CalOES's text alert. An analysis using high-resolution meter data can provide insights into electricity use that is not controlled by networked thermostats.

The limited effects of the CalOES text alert indicated by the matching method may also reflect heterogeneous responses in AC usage among California residents. Our matching DiD analysis captures the average response of households that remain after matching. However, households with certain attributes may respond differently to the alert, including differences in income, age, and baseline thermostat interactions. For example, low-usage households often use their AC in ways that utilities do not anticipate (Deumling, Poskanzer, and Meier 2018). Such households may respond strongly to the alert if they frequently turn off their AC. If only a small subset of households responds strongly while the majority responds little, statistically significant average effects may be difficult to detect. Alternatively, the matched sample used in our DiD analysis may consist primarily of households that do not respond strongly to the alert. Our sample consists of households that purchased networked thermostats. These households may be wealthier and less responsive to requests to conserve electricity. In addition, they may spend more time away from home than the general population, as the ability to control thermostats remotely and automatically may be particularly attractive to such households. These possibilities suggest that future research should place greater emphasis on heterogeneous responses and identify the household characteristics associated with strong behavioral reactions.

This study presents four policy implications. First, our AC temperature sensitivity analysis indicates that cooling demand will continue to rise as heat waves become more frequent and intense. Consequently, grid operators will face greater challenges in balancing electricity demand and supply. Second, our estimation of the government's energy-saving call reveals that moral suasion is not always effective in reducing electricity demand from AC usage. Thus, incentivized demand responses may be more effective, though such dynamic pricing is currently unpopular. Third, combining our results from the AC temperature-sensitivity analysis with the estimated effects of the government text messaging suggests that grid operators need new policy tools to balance electricity demand and supply during heat waves. A promising solution is to automate AC responses to the government's calls to save energy. Fourth, optimal sizing of AC systems may help mitigate sharp increases in AC use during extreme temperatures, as our results indicate that oversizing contributes to such increases. Optimal sizing is also policy-relevant, as oversizing generally increases the installation, maintenance, and operating costs of AC systems (Reddy and Claridge 1993; Chiu and Krati 2021). Therefore, aligning installed capacity with its optimal level may reduce household expenditures.

Conclusion

In this study, we utilize networked thermostat data to examine cooling demand during the 2022 California heat wave. Specifically, we investigate (1) whether cooling demand increases further during more intense heat waves, and (2) what drives the reduction in cooling demand after CalOES's text alert. To address the first question, we measure AC sensitivity to extreme outdoor temperatures up to 110°F. We found that AC electricity consumption continues to rise without saturation, even at extremely high temperatures that have not been examined in previous studies. Additionally, household behavior, as measured by setpoint changes, does not respond to high outdoor temperatures, suggesting most residential ACs maintain excess capacity. To address the second question, we analyze how AC usage responds to the government's request for immediate electricity conservation issued during the heat wave. The matching DiD method detects a minimal reduction after the request. Therefore, ACs controlled by networked thermostats alone cannot explain the system-wide drop after the CalOES's text alert.

Heat waves are expected to become more frequent and intense (Calvin et al. 2023). Our study indicates that electricity consumption from cooling demand will increase as heat waves intensify, further stressing the grid. Therefore, grid operators need to develop more effective demand response programs. The Michigan case, where the government's request to reduce heating demand was effective (Brewer and Crozier 2025), suggests that making target behaviors more feasible can enhance effectiveness. Furthermore, as AC usage becomes automated, it may become less responsive to government conservation measures. Therefore, incorporating automated responses to these requests into networked thermostats will be effective. Aligning AC system capacity with optimal levels will also be effective to mitigate sharp increases in AC use during extreme temperatures.

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