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Abstract

Time-of-use (TOU) electricity prices are increasingly being adopted to reduce consumption during the higher marginal cost afternoon hours. There is ample evidence that TOU rates reduce average consumption during the peak price hours of the day, but it is unknown how these energy savings are distributed across days. Using a unique dataset from households with smart thermostats, we find that adopting TOU rates causes large decreases in peak period AC usage, resulting in energy savings that are concentrated on the hottest, highest demand days when the benefits of conservation are the greatest.

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1 Introduction

The marginal cost of electricity varies substantially within and across days, peaking throughout much of the US during the late afternoon on the hottest days, when demand for space cooling peaks (Auffhammer, Baylis and Hausman, 2017). Despite this variation in the marginal cost, the vast majority of consumers face time-invariant electricity prices.[1] Economists have long advocated for time-varying prices that reflect the marginal cost (e.g., Boiteux (1960), Kahn (1970)), with perhaps the simplest form being time-of-use (TOU) rates. While TOU rates do not vary across days, they do expose consumers to a higher price for electricity consumed during the peak demand hours of the day. Ample evidence demonstrates TOU rates reduce average consumption during the peak price hours.[2] However, it is unknown how these peak period energy savings are distributed across days. In this paper, we examine whether the peak period energy savings achieved by TOU rates are concentrated on the hottest, highest demand days when the cost savings are the greatest.

Reducing peak period electricity consumption on the hottest days provides sizable benefits. Not only is less production required from generating units with high operating costs and pollution damages (Porzio et al., 2023), the long-run capital costs incurred to ensure sufficient generation, storage, and transmission capacity exists to meet the peak system demand are also reduced.[3] Moreover, reducing peak period consumption on high demand days can avoid widespread service disruptions. For example, a September 2022 heatwave in California pushed the load in the market overseen by the California Independent System Operator (CAISO) to record levels. To avoid the need for widespread rolling blackouts, an emergency text message was sent to millions of Californians urging them to "conserve energy now to protect public health and safety." This message was credited with reducing the system load

[1] Borenstein and Bushnell (2022) highlight that, from 2014-2016, only 4% of residential customers in the US faced time-varying electricity rates, the vast majority being TOU rates.

[2] For literature reviews on the impacts of TOU and dynamic pricing, see Faruqui and Sergici (2010), Faruqui, Sergici and Warner (2017), Dutta and Mitra (2017), and Harding and Sexton (2017).

[3] Boomhower and Davis (2020) highlight how energy efficiency investments that deliver energy savings during the periods with peak system demand provide far greater returns.

by 4%, likely averting a costly "broader grid disturbance" according to CAISO's president.[4] Our results highlight that consumers' response to default TOU rates can achieve comparable reductions in the peak system load.

How TOU-induced peak period energy savings are distributed across days is determined in part by which energy service(s) consumers reduce in response to the peak period price. In the region studied in this analysis, Sacramento, CA, one of the main energy services consumed is indoor cooling, accounting for approximately 20% of the residential electricity usage (Novan, Smith and Zhou, 2022). If consumers respond to TOU rates by reducing air conditioning (AC) use during the peak hours, then the peak period energy savings may be concentrated on the hottest days, when the cost savings are the largest. In contrast, if consumers reduce energy services that are uncorrelated with the daily temperature (e.g., dishwasher, laundry), the resulting peak period savings will be more uniformly distributed across days. Again, while there is ample evidence demonstrating that consumers reduce consumption in response to higher electricity prices, there is little information surrounding the elasticity of demand for individual energy services like cooling.[5] Moreover, even if cooling is responsive to the peak price increase, it is unknown whether the price incentive will be strong enough to induce meaningful reductions in AC use on the very hottest days, when the private benefits of indoor cooling will be the greatest.

To explore whether TOU rates affect energy use differently across days, we examine how residential consumers served by the Sacramento Municipal Utility District (SMUD) responded to a transition to TOU rates. SMUD is one of the largest publicly owned electric utilities in the US, supplying 5% of the electricity consumed in California (APPA, 2022). Between October 2018 and May 2019, SMUD transitioned their 1.5 million residential consumers from a default rate plan with time-invariant prices to a default TOU rate plan that increased the price per kilowatt hour (kWh) by 100% from 5pm to 8pm on summer weekdays.

[4] An article in the *Los Angeles Times* (Toohey and Petri, Sept. 7, 2022) describes the event.

[5] Alberini and Filippini (2011) and Miller and Alberini (2016) review the literature providing estimates of the elasticity of demand for residential electricity consumption aggregated across all energy services.

We first examine whether the default TOU rates caused households to reduce AC use during the peak price hours. To do so, we take advantage of a dataset from Ecobee, a smart thermostat company. Ecobee encourages their customers to opt into their "Donate Your Data" program, making their anonymized data available to researchers. Through this program, we observe 5-minute interval AC runtimes and thermostat set points during 2018 and 2019 for 287 households located within, as well as just outside of, SMUD's service territory. Exploiting the fact that default TOU rates were not adopted outside of SMUD during our study period, we use a difference-in-difference strategy to quantify the impact of TOU rates. We find that the switch to TOU rates caused SMUD households to increase their thermostat set point from 5pm until 8pm on summer weekdays by an average of 1.04°F. As a result, the average peak period AC runtimes in SMUD households fell by an average of 3.2 minutes per hour, a 14% decrease, from 5pm to 8pm on summer weekdays. This response implies an elasticity of demand for AC during the peak period equal to -0.14. Importantly, we find that the reduction in AC runtimes among the Ecobee households is greatest on the hottest days, when California's demand peaks. A back-of-the-envelope estimate suggests that, if AC use responds similarly across SMUD's population of residential consumers, we would observe a 4% reduction in the total amount of electricity consumed (load) from SMUD during the peak hours on the hottest, highest demand days.

Of course, the Ecobee households are far from randomly selected. Not only have they chosen to share their data, they also own a smart thermostat.[6] There are numerous reasons why the impact of TOU rates could vary with ownership of a smart thermostat. Households can program the thermostats to follow pre-determined cooling schedules and they can be operated remotely. Given these features, it is certainly possible that the effect of TOU rates is more pronounced among the households that selected to install them. Alternatively, households with smart thermostats may be wealthier on average and have less elastic responses to electricity prices.

[6]As of 2018, only 11% of US households had smart thermostats (King, 2018).

To further explore whether the switch to default residential TOU rates achieved meaningful energy savings on the hottest, highest demand days, we analyze how SMUD's total hourly load changed from 2018 to 2019. Controlling for temperature differences across years, we find robust evidence that SMUD's load fell by an average of nearly 150 MWh per hour during the peak period on summer weekdays. Providing strong support that this was caused by the TOU rates, we find no evidence of similar load decreases on summer weekends or non-summer weekdays. Consistent with AC reductions being a key driver of these peak period energy savings, we find that the peak period load reductions are more than twice as large on the hottest summer days compared to mild summer days. In line with our estimates of the AC use reductions from the Ecobee dataset, our analysis of the aggregate load data again suggests that the cooling reductions caused by the switch to default residential TOU rates result in a 5% reduction in SMUD's peak period load on the hottest summer weekdays.

Our analysis contributes to the literature studying time-varying electricity prices.[7] While there is clear evidence households reduce consumption during peak price periods, the existing literature provides limited evidence surrounding which energy services consumers reduce. The existing evidence stems largely from critical peak pricing (CPP) studies. Faruqui and George (2005), Wolak (2007), and Burkhardt, Gillingham and Kopalle (2019) each examine CPP programs that increase the peak period price by a factor of five on a select number of days – typically the highest demand days. Faruqui and George (2005) and Wolak (2007) provide indirect evidence that the CPP programs reduce peak period AC use (e.g., larger average energy savings occur in hotter locations and among households with central AC units). Examining appliance-level data, Burkhardt, Gillingham and Kopalle (2019) find reductions in AC use account for much of the peak savings. However, there is no comparable evidence surrounding whether TOU rates, which do not vary across days, and which do not increase peak period prices by 400%, induce meaningful reductions in AC use. Our results demonstrate that, even the modest peak-period price increases adopted by SMUD

[7]For a list of studies focused on dynamic electricity pricing through 2015, see Enright and Faruqui (2015).

were sufficient to encourage sizable reductions in cooling on the hottest days.

Similar to our analysis, Blonz et al. (2021) also use data from Ecobee smart thermostats to examine how households exposed to TOU rates alter their AC use.[8] However, rather than focusing on the effect of TOU rates, the authors estimate how automating the response of AC use to time varying prices alters the impact of TOU rates.[9] They find that automation combined with TOU rates leads to meaningful reductions in peak period AC use. Our results reveal that TOU rates alone, even in the absence of automation, lead to sizable reductions in peak period AC use, particularly on the hottest days.[10]

The remainder of the paper proceeds as follows. Section 2 describes SMUD's TOU rates and the data. Section 3 quantifies how AC use responds to default TOU rates and Section 4 examines how SMUD's aggregate hourly load changes. Section 5 concludes.

2 Background and Data

2.1 Default TOU rates

Roughly half of the energy supplied by SMUD is consumed by their 1.5 million residential consumers (SMUD, 2019). Prior to October 2018, SMUD's default residential rate plan charged \$0.131 for each kWh consumed during the summer months (June through September) and \$0.1145 for each kWh consumed during all other months. Although the per kWh rate varied slightly across seasons, there was no variation within a day.

In contrast, the cost SMUD incurs to provide electricity to consumers varies from hour to hour. To get a sense of the magnitude of the within-day variation in the cost of procuring energy, the middle panel of Figure 1 displays the average wholesale price (\$/MWh) by hour-of-day in the Real-Time Market (RTM) overseen by CAISO from June through September

[8] Related work by Brewer and Crozier (2023) utilizes Ecobee data to examine how households respond to calls for conservation.

[9] Gillan (2017) and Bollinger and Hartmann (2020) also find automation increases household's responsiveness to time-varying prices. Related work demonstrates that providing real-time consumption information increases households' responsiveness to dynamic price signals (e.g. Jessoe and Rapson (2014)).

[10] Ecobee began rolling out the Eco+ automation software that was examined by Blonz et al. (2021) during 2019, but none of the households in our sample were using Eco+ during our sample period.

of 2019.[11] From 5pm until 8pm, the average RTM price was \$65/MWh – more than double the average of \$27/MWh across all other hours.

In an effort to reduce consumption during this higher-cost window of time, and potentially shift consumption to the lower-cost periods of the day, SMUD began transitioning their residential consumers to a new default TOU rate plan beginning in October 2018.[12] By May of 2019 the transition was complete and the vast majority of SMUD's residential customers were exposed to the new TOU rates.[13]

TOU rates applied only on non-holiday weekdays, and the intraday price variation was largest during the summer (June through September). During the three peak hours (5pm-8pm) in summer, households on the default TOU plan paid \$0.2835 per kWh, compared to \$0.1166 per kWh during off-peak hours (midnight until noon). During summer mid-peak hours (noon until 5pm and 8pm until midnight), the price was \$0.1611 per kWh (top panel of Figure 1). During the non-summer months (October through May), the TOU variation was small. Households paid \$0.1338 for each kWh consumed from 5pm until 8pm and \$0.0969 for each kWh consumed during all other hours. In all seasons, the price remained constant across hours on weekends and holidays.[14]

There is overwhelming evidence demonstrating that TOU rates can reduce the average consumption during the peak period. Indeed, an earlier pilot study conducted by SMUD found that a similar default TOU rate structure reduced households' average consumption during the peak price hours by 5% (Potter, George and Jimenez, 2014; Fowlie et al., 2021). What isn't clear, however, is how these reductions in peak period consumption are achieved (i.e. what energy services are being reduced during peak hours) and consequently, how the energy savings are distributed across days. How the peak period energy savings are distributed

[11] While much of SMUD's energy is purchased through bilateral contracts, we would expect the contracts to reflect the market value of energy revealed in the wholesale market.

[12] SMUD's commercial/industrial consumers moved to TOU rates several years earlier.

[13] We do not observe the share of residential consumers that opt out of the default TOU rates, but an earlier pilot study (Potter, George and Jimenez, 2014) found the opt out rate was less than 3%.

[14] Very similar default residential TOU rate plans have subsequently been adopted by California's investor owned utilities. A similar default TOU plan has also been in place for many years in Ontario, Canada. See Miller, Golab and Rosenberg (2017) for an evaluation of the average impacts of the Ontario TOU program.

across days matters because the cost of supplying energy during the peak period varies substantially across days. On days when the demand for electricity throughout California and the surrounding western states is high, the benefits of reducing peak period consumption will be the greatest. Much of the day-to-day variation is regional demand stems from the need for temperature control, with consumption and wholesale energy prices peaking on the hottest days. The bottom panel of Figure 1 highlights that, during 2019 summer weekdays when the daily average temperature in Sacramento was between $72°F$ and $76°F$, the average RTM price between 5pm and 8pm was $48/MWh.[15] In contrast, on weekdays with an average temperature above $84°F$, and daily maximum temperatures typically exceeding $100°F$, the average RTM price during the peak hours jumped to $184/MWh.

2.2 Household AC use

To examine whether SMUD's residential TOU rates reduce peak period consumption on the hottest days, we focus on three different outcome variables. The first two outcome variables are observed from a set of households that have installed an Ecobee programmable thermostat and have chosen to participate in Ecobee's "Donate Your Data" (DYD) program. For this set of homes, at the 5-minute interval level, we observe (a) the amount of time each household's AC unit is running and (b) the thermostat set point households have set.[16] When the indoor temperature drops below this set point, the AC unit will not turn on unless the households override the programmed cooling schedule. Restricting our sample to the households for which we observe AC use during the summer months (June through September) of 2018 and 2019, we identify 132 households in SMUD's service territory.

In addition to the households located in SMUD's service territory, we also identify a set of control households from the DYD dataset that are located in a set of nearby counties.

[15] The daily average temperature is the simple average of the hourly temperatures recorded by NOAA at the Sac. International Airport.

[16] For households with single-stage AC units, the share of time the AC compressor is running will be directly proportional to the amount of electricity consumed for cooling. For households with multi-stage AC units that can operate at different speeds, the compressor runtime may not be perfectly correlated with electricity consumption. If the increase in peak prices results in a reduction in the speed at which the AC units are operating, as opposed to simply the runtimes, then our subsequent estimates will understate the impact of TOU rates on the amount of energy used for cooling.

To ensure the control households are exposed to a similar climate as the SMUD households, we limit our control sample to households located in the Central Valley counties which the California Energy Commission (CEC) designates as having a Climate Zone (CZ) with similar climates to Sacramento's – counties in Climate Zones 12 and 13, which include the Central Valley counties immediately west of Sacramento County and extending south down the Valley.[17] Restricting our control households to come from the two specified CZs, we identify 155 additional households in the Ecobee DYD dataset. Table A1 summarizes a variety of self-reported characteristics of the SMUD and non-SMUD samples. Roughly 70% of both samples are detached, single-family homes, with the remaining being a combination of townhouses and condominiums. The SMUD premises tend to be older, with an average building age of 30 years as opposed to 20 years for the non-SMUD sample. The average square footage, number of floors, and number of occupants are very similar across the two samples. Similarly, both samples have had their Ecobee thermostats installed for similar periods of time – the mean and mode installation year was 2016, with roughly 10% of each sample installing their thermostat in the period from January through April of 2018.

Each of 155 non-SMUD households are located in Pacific Gas & Electric's (PG&E) service territory. Unlike SMUD, PG&E had not adopted default TOU rates in 2018 or 2019.[18] Instead, PG&E customers had the option to voluntarily enroll in a variety of non-default TOU rate programs.[19] During 2018, 9% of PG&E's residential customers had opted into

[17]The CEC classifies California counties into 16 different Climate Zones based on their typical annual heating and cooling degree distributions. These Climate Zone designations are used for a variety of purposes (e.g., building energy efficiency standards differ across Climate Zones). Sacramento County falls in Climate Zone 12, the central portion of California's Central Valley. While slightly warmer, Climate Zone 13, which is the southern portion of the Central Valley, has similar climate patterns to Climate Zone 12. The non-SMUD sample construction is described in greater detail in Appendix A.

[18]During summer 2018 and 2019, the vast majority of households in PG&E's service territory were enrolled in the standard residential tiered rate schedules. Under these tiered rate schedules, households were assigned a monthly baseline usage level that varied based on the climate zone. In summer 2018, households on this default rate schedule paid $0.21169/kWh on each kWh up to the baseline usage level, $0.27993/kWh on each kWh beyond their baseline usage level up to 400% of their baseline, and $0.43343/kWh on each kWh beyond 400% of the baseline usage level. In summer 2019, the per kWh prices for consumption between 0-100% of the baseline, 100-400% of the baseline, and above 400% of the baseline increased slightly to $0.22281/kWh, $0.28039/kWh, and $0.49124/kWh.

[19]The TOU rate structure options differed slightly across options, however each created a peak-price period between 3-8pm or 4-9pm. Summaries of the historical PG&E rate options can be found here,

a TOU rate program. In 2019, this increased to 11% of PG&E's residential customers.[20] Ideally, we would be able to observe which, if any, of the non-SMUD households in our Ecobee sample have opted into a TOU rate structure. Given that this is not possible, we instead lean on the fact that there was very limited growth in PG&E's TOU programs between 2018 and 2019 and assume that none of the control households switch from non-TOU rates into a TOU program between 2018 and 2019. Importantly, if PG&E households in our control sample do switch into TOU rates during our sample period, then our subsequent estimates will weakly understate the impacts of SMUD's default TOU rates.

The top left panel of Figure 2 displays the average minutes per hour the SMUD households' AC units are operating on summer weekdays during 2018 and 2019. Outside of the three-hour window from 5pm until 8pm, the AC runtimes for the SMUD homes are higher on summer weekdays during 2019 compared to 2018. This is driven largely by the fact that the summer of 2019 was considerably warmer.[21] In contrast, the AC runtimes were effectively unchanged during the peak price hours from 5pm until 8pm, providing clear evidence of a reduction in peak period AC use in response to the 2019 TOU rates.

For comparison, the top right panel of Figure 2 displays the 2018 and 2019 average hourly AC runtimes for the non-SMUD households.[22] Like the SMUD households, these non-SMUD households all experienced the same, warmer 2019 summer. As a result, we again see the increase in AC runtimes in 2019 compared to 2018. However, as these households were not uniformly switched to a default TOU rate plan, there is no observed decrease in the AC runtimes between 5pm and 8pm. It is worth noting that, while the non-SMUD households located in counties immediately surrounding SMUD's service territory (e.g., the non-SMUD

https://www.pge.com/tariffs/en/rate-information/electric-rates.html.

[20]Information on the number of customers enrolled in each rate program are provided annually through FERC Form 1.

[21]Table A1 reports summary statistics of the average daily temperature measured by the NOAA weather station at the Sacramento International Airport. The average daily temperature, during summer 2019 was $1.5°F$ warmer than the average daily temperature during summer 2018.

[22]Figure A1 displays the difference between the average hourly AC runtimes between the SMUD and non-SMUD households separately for 2018 and 2019. Outside of the peak price hour, and the hour immediately preceding the beginning of the peak price period, the differences between the SMUD and non-SMUD households' AC usage patterns are effectively unchanged between 2018 and 2019.

households in Yolo and San Joaquin Counties) experienced nearly identical daily average temperatures as the SMUD households, differences in the daily temperatures between the SMUD and non-SMUD households do emerge for non-SMUD households located farther south in the slightly warmer Climate Zone 13. In particular, Table A1 highlights that the average daily temperature across the full sample of non-SMUD households is 4°F higher. Ultimately, we will address these differences in our empirical specification using a combination of premise-level fixed effects and flexible temperature controls.

While the top panel of Figure 2 provides clear evidence that the TOU rates reduce peak period AC use, the sample of households is likely non-representative. Not only have these households selected into sharing their data through Ecobee's DYD program, they have also selected to install a smart thermostat. As of 2020, 14% of the thermostats installed in single-family homes in the US were smart thermostats, 34% were manual (i.e. non-programmable) thermostats and the remaining 51% were programmable, but did not have the features commonly found with smart thermostats.[23] Like a regular programmable thermostat, households in our sample can use their Ecobee thermostats to create daily cooling schedules (e.g., the thermostat set points can be scheduled to differ by hour of day, as well as across days of the week). Moreover, the Ecobee thermostats (and the cooling schedules) can be adjusted remotely. In addition, households have the option to allow their Ecobee thermostats to automatically adjust the thermostat set points if motion sensors do not detect movement in the house. Consequently, changes in AC use among this subset of households may not be representative of how the larger population of SMUD households responds to TOU rates.

2.3 Aggregate hourly SMUD load

To further examine whether the default TOU rates provide peak-period energy savings on the hottest days, we also examine whether there is a discernible change in the aggregate level of electricity consumed (i.e. the load) in SMUD's service territory. From the Federal Energy Regulatory Commission's Form-714, we observe SMUD's hourly total load. The top

[23]2020 appliance penetration statistics come from the US Energy Information Administration's 2020 Residential Energy Consumption Survey (RECS).

left panel of Figure 4 displays SMUD's average hourly load on summer weekdays during 2018 and 2019. The top right panel displays the percentage changes in these average hourly loads across the two summers. Consistent with summer 2019 being hotter, the average hourly SMUD load is higher during each hour of the day outside of the 5pm until 8pm peak window. In contrast, during the three peak hours, the average hourly load is lower in 2019 than 2018, again suggesting that the default TOU rates reduce peak period consumption.

To visualize how the peak period load change differs across days, the bottom left panel of Figure 4 plots the average hourly peak period load for each weekday in 2018 and 2019 against the daily average temperature. The figure reveals a pattern consistent with the default TOU rates meaningfully reducing AC use. On days with average temperatures below $65°F$, when little to no cooling will be demanded, the average hourly peak period load is consistently within 100 MWhs of the average hourly peak period load in 2018. In contrast, on the hottest days, SMUD's average weekday peak-period load fell by more than 200 MWhs in 2019 relative to 2018. If this reduction in the slope between the peak period load and the temperature was driven by factors other than the switch to TOU rates – e.g., building insulation improvements, reductions in demand for cooling – then we would expect to see a similar pattern in the relationship between peak period load and temperature on weekends as well. However, there is no similar change in the relationship between the peak period load and temperature on weekends (see appendix Figure A4).

In addition to examining how the level of the peak period load changes after the adoption of TOU rates, our subsequent empirical analysis also quantifies how the within-day variation in load responds to TOU rates. The bottom right panel of Figure 4 introduces our measure of the within-day load variation—the spread between the average hourly load during the peak hours and the mid-peak hours of each day. On days with average temperatures below $65°F$, when little to no electricity will be used for cooling, the relationship between the peak to mid-peak spread and the daily temperature is identical across 2018 and 2019. In contrast, on days with average temperatures above $75°F$, when demand for cooling is at its highest, the peak to mid-peak spread falls by roughly 100 MWh in 2019 relative to 2018, consistent with peak period AC use falling in response to default TOU rates.

3 Impact of TOU Rates on AC Use

3.1 Change in AC runtime

To identify how AC usage changes in response to the TOU rates, we use a difference-in-differences approach. Using our Ecobee dataset, we simultaneously estimate the following model 24 times, once for each hour of the day, using observations from weekdays during June through September of 2018 and 2019:

$$\text{Runtime}_{i,h,d} = \beta_h \cdot \text{Post}_d \cdot \text{SMUD}_i + \boldsymbol{\theta}_{1,h} \cdot \mathbf{T}_{i,d} + \boldsymbol{\theta}_{2,h} \cdot \mathbf{T}_{i,d} \cdot \text{SMUD}_i + \alpha_{i,h,m} + \mu_{d,h} + \varepsilon_{i,h,d}, \quad (1)$$

where $\text{Runtime}_{i,h,d}$ is the number of minutes household i's AC unit runs during hour h on day d, Post_d is an indicator variable that equals one for observations from 2019 (following SMUD's switch to default TOU rates) and 0 for observations from 2018 (prior to the adoption of the default TOU rates), SMUD_i is an indicator for homes in SMUD's service territory, $\alpha_{i,h,m}$ is a household fixed effect that is allowed to vary flexibly across hour-by-month-of-year, and $\mu_{d,h}$ is a day-of-sample fixed effect that is allowed to vary flexibly across hours.

To control for temperature-driven differences in AC use, we model the hourly AC runtime as a function of the daily average temperature in the region where each household is located, $\text{Temp}_{i,d}$. For the SMUD households, we use the daily average temperature recorded at the Sacramento International Airport.[24] For non-SMUD households, we use the daily average temperature recorded at the NOAA weather station located closest to each household's city of residence.[25] The temperature enters the model through $\mathbf{T_{i,d}}$, a piecewise linear spline with

[24] With very little elevation difference across the SMUD service territory, there is very little spatial variation in the daily temperature. Novan, Smith and Zhou (2022) also highlight that, in Sacramento, the hourly temperature during any given hour of the day is highly correlated with the daily average temperature. To ensure common support over the weekday temperatures experienced by SMUD households during 2018 and 2019, we trim the sample to days where the average Sacramento temperature is between $64°F$ and $80°F$.

[25] Information on the NOAA stations used is summarized in Appendix A.

knot points at 70°F and 75°F. Specifically, $\mathbf{T_{i,d}}$ represents the following 3×1 vector:

$$\mathbf{T_{i,d}} = \begin{bmatrix} min(\text{Temp}_{i,d}, 70) \\ min\Big(max(\text{Temp}_{i,d} - 75, 0), 75 - 70\Big) \\ max(\text{Temp}_{i,d} - 75, 0) \end{bmatrix}. \tag{2}$$

To allow for average AC runtimes in SMUD and non-SMUD households to respond differently to the daily temperature, we also interact $\mathbf{T_{i,d}}$ with the SMUD indicator.

In the model specified by Eq. 1, β_h is the key parameter of interest. If the change in average AC runtimes from summer 2018 to summer 2019 differed in SMUD households relative to the non-SMUD households, this will be captured by our estimates of β_h. To interpret our estimate of β_h as the causal effect default TOU rates have on AC runtimes in the SMUD households during hour h, we must assume that, aside from regional temperature differences, no other time-varying determinants of AC demand systematically differ for SMUD households relative to the non-SMUD households. Put differently, absent the switch to default TOU rates, after controlling for temperature differences, the change in average hourly AC runtimes from 2018 to 2019 would be identical across SMUD and non-SMUD homes. This is clearly a strong assumption, and one that we cannot directly test given the fact that we do not observe changes in non-temperature-driven determinants of AC demand (e.g., household income; energy efficiency investments). However, there are key features of the rate change that enable us to conduct two falsification tests to indirectly test our identifying assumption.

First, if the adoption of the default TOU rates cause AC use to fall in SMUD homes, we expect to see these decreases largely confined to the peak hours. Alternatively, if decreases in peak period runtimes are caused by factors beyond TOU rates (e.g., home retrofits, reductions in cooling demand), we would expect to see decreases outside of the peak period as well. The bottom left panel of Figure 2 displays the point estimates of β_h from Eq. 1 for summer weekdays.[26] The only significant changes occur during the peak hours, with

[26] The confidence intervals are robust to clustering at the household level.

average AC runtimes in the SMUD homes falling by roughly 3 minutes each hour following the adoption of the default TOU rates.

Second, if the decrease in peak period runtimes was caused by factors such as energy efficiency improvements or reductions in cooling demand, we would expect to see similar reductions occur during the 5pm through 7pm hours on weekends, when the TOU rates are not in affect. Simultaneously estimating Eq. 1 24 times (for each hour of the day) using observations from summer weekends, we find no significant changes in AC runtimes during the peak hours (bottom right panel of Figure 2).

To summarize our estimates, we aggregate the hourly observations into three daily, household level outcome variables – the average hourly AC runtime during period p of day d ($\text{Runtime}_{p,d}$), where the three periods are the peak hours (5pm through 7pm), the mid-peak hours (noon to 5pm and 8pm to midnight), and the off-peak hours (midnight to noon). Using these average hourly AC runtimes as the new dependent variables, we simultaneously estimate the following difference-in-difference specification separately for each period of the day (peak, mid-peak, and off-peak) on weekdays or weekends using Summer 2018 and 2019 observations:

$$\text{Runtime}_{i,p,d} = \beta_p \cdot \text{Post}_d \cdot \text{SMUD}_i + \boldsymbol{\theta}_{1,p} \cdot \mathbf{T}_{i,d} + \boldsymbol{\theta}_{2,p} \cdot \mathbf{T}_{i,d} \cdot \text{SMUD}_i + \alpha_{i,m,p} + \mu_{d,p} + \varepsilon_{i,p,d}, \quad (3)$$

where SMUD_i is again an indicator for households in SMUD's service territory, Post_d is an indicator for observations from 2019, $\mathbf{T}_{i,d}$ is the temperature spline specified by Eq. 2, and $\alpha_{i,m,p}$ and $\mu_{d,p}$ are now premise-by-month-by-period and period-by-day-of-sample fixed effects.

The first two columns of Table 1 display estimates of β_p from Eq. 3 for each of the three periods of the day (peak, mid-peak, and off-peak) on weekdays, when the TOU rates were in effect during 2019, and on weekends, when the TOU rates were not in effect at any point. Consistent with Figure 2, SMUD households' AC runtimes during the peak period on weekdays fall by an average of 3.20 minutes per hour. To explore whether the reduction in peak runtime differs with the daily temperature, we split the sample into weekdays with average temperatures in Sacramento below $69°F$, $69°F$ to $75°F$, and above $75°F$. Simultaneously estimating Eq. 3 separately for each subset of days, we find the reduction in peak period runtime is more pronounced on hotter days.[27] On weekdays with average temperatures greater than or equal to $75°F$, the hottest 30% of summer days, we find the average peak runtime falls by 4.50 minutes per hour, a 15% reduction relative the average peak period runtime on summer 2019 weekdays.[28]

In addition, to explore the importance of using non-SMUD households to control for unobserved, time-varying determinants of AC demand, we also estimate a model that does not pool observations across SMUD and non-SMUD households. Specifically, we estimate the following model separately for SMUD and non-SMUD households using weekday (or weekend) observations from Summer 2018 and 2019:

$$\text{Runtime}_{i,p,d} = \beta_p \cdot \text{Post}_d + \boldsymbol{\theta}_p \cdot \mathbf{T}_d + \alpha_{i,m,p} + \varepsilon_{i,p,d}, \tag{4}$$

where β_p now captures how AC runtimes change within SMUD (or within non-SMUD) households from Summer 2018 to Summer 2019, not controlling for any time-varying determinants of AC demand other than the outdoor temperature and regular, monthly patterns in household-specific usage (through the inclusion of a premise-by-month-by-period fixed effect, $\alpha_{i,m,p}$). Note that by not pooling across SMUD and non-SMUD households, Eq. 4 can no longer include a day-of-sample fixed effect.

The last four columns of Table 1 present estimates of β_p from Eq. 4 separately for

[27]Column 1 of Table A2 displays estimates from an augmented version of Eq. 3. The augmented model tests for heterogeneity in the average treatment effect across different temperatures by including the interaction between $\text{Post}_d \cdot \text{SMUD}_i$ and $(\text{Temp}_{i,d} - 64°\text{F})$. Consistent with the results displayed in the first column of Table 1, the reduction in average hourly peak-period AC runtimes increases significantly as the daily temperature increases above 64°F. Column 3 of Table A2 presents estimates of the same model using the natural log of the peak-period runtime as the dependent variable. The results demonstrate that the percentage reduction in peak period runtimes grows slightly as the average daily temperature increases.

[28]The average peak period runtime on 2019 weekdays with temperatures above $75°F$ was 25.25 min/hour.

SMUD and non-SMUD households on weekdays and weekends. The results reveal that, after controlling for temperature differences across years, the only significant reduction in weekday AC runtimes from 2018 to 2019 occurred during the peak weekday hours among SMUD households. The fact that AC runtimes did not change significantly among the non-SMUD households during the peak price period demonstrates that the key point estimates from the diff-in-diff specifications (Eq. 1 and Eq. 3) are not driven by unobserved factors that simply caused peak-period AC usage to increase by relatively more in non-SMUD homes relative to SMUD homes. Instead, the results from this simpler model provide additional evidence demonstrating that the switch to default TOU rates caused a sizable decline in the average peak-period AC runtimes among the SMUD households.

3.2 Change in thermostat set points

To understand how the SMUD households achieve the reduction in peak period AC usage, we examine how households alter their thermostat set points following the adoption of the TOU rates. The thermostat set points largely dictate the frequency with which the AC units will be operating. When the temperature in the house is below this set point, the AC unit will not turn on unless the household manually overrides the program.[29] Households can change the set points in two ways. First, they can alter their predetermined schedules they have created for the set point to follow. Second, households can manually (physically or remotely) adjust the set points in real time. Intuitively, if the households are responding to the TOU rates by altering the predetermined schedules, then we would expect to see discontinuous changes in the average set points at the start and end of the peak pricing period. Alternatively, if the households are largely achieving reductions in peak AC usage by manually adjusting their set points in real-time, then we may not expect to observe sharp changes in the average set points between pricing periods.

[29] In addition to the 5-minute interval set point, we also observe when households manually override ("hold") their pre-scheduled set points to either keep their AC unit running or to prevent their AC unit from turning on. Re-estimating Eq. 5 using the binary indicator for whether a household uses the 'hold' override option during a 5-minute interval, we find no evidence of significant changes in the frequency of holds following the adoption of TOU rates.

To examine how the set points change, we take advantage of the fact that we observe each household's set point at the 5-minute interval level.[30] To quantify how the daily profile of set points change in response to the TOU rates, we simultaneously estimate the following model 288 times, once for each 5-minute interval of the day, using observations from summer (June through September) weekdays:

$$\text{Set}_{i,t,d} = \beta_t \cdot \text{Post}_d \cdot \text{SMUD}_i + \boldsymbol{\theta}_{1,t} \cdot \mathbf{T}_{i,d} + \boldsymbol{\theta}_{2,t} \cdot \mathbf{T}_{i,d} \cdot \text{SMUD}_i + \alpha_{i,t,m} + \mu_{d,t} + \varepsilon_{i,t,d}, \quad (5)$$

where $\text{Set}_{i,t,d}$ is the 5-minute-level thermostat set point (measured in °F) for household i during 5-minute interval t of day d. As before, Post_d is an indicator variable that equals one for observations from 2019 and SMUD_i is an indicator for homes in SMUD's service territory. $\alpha_{i,t,m}$ is now a household fixed effect that is allowed flexibly vary across 5-minute intervals by month-of-year and $\mu_{d,t}$ is a day-of-sample fixed effect that is allowed to vary flexibly across 5-minute intervals. The estimates of β_t represent the average change in SMUD set points during interval t on summer weekdays following the adoption of TOU rates.

The top panel of Figure 3 displays the 288 point estimates of β_t from Eq. 5.[31] Following the adoption of the TOU rates, there is a significant, and very stable (roughly 1°F), increase in the average set point across all of the peak price intervals. Importantly, this increase in the set point occurs discontinuously at the start of the peak price window (at 5pm), with a corresponding discontinuous drop at the end of the peak price window (at 8pm). While less pronounced, the top panel of Figure 3 also provides evidence of a smaller, discontinuous increase in the average set point at the beginning of the mid-peak price period (at noon). Moreover, there is also clear evidence of households reducing the set point (i.e. pre-cooling) in the hour immediately prior to the peak price window beginning. Ultimately, the clear, discontinuous changes in set points are consistent with households largely responding to the

[30] To understand the relative magnitude of the subsequent set point changes, Figure A2 displays the average 5-minute weekday set point profile among SMUD households during summer 2018 and 2019. Between 5pm and 8pm on summer weekdays during 2018, the average set point among the SMUD households was 77.7°F.

[31] The 95% confidence interval around each point estimate is robust clustering at the household level.

adoption of the TOU rate structure by altering their daily schedule for their set point.

To visualize how these abrupt set point changes discontinuously alter AC runtimes at the beginning and ending of the peak price period, we reestimate Eq. 5 for each 5-minute interval of the day using the interval AC runtime (measured as the share of time a household's AC unit is running during the 5-minute interval) as the dependent variable.[32] The bottom panel of Figure 3 highlights that the 1°F increase in peak period set points causes AC usage to discontinuously fall by 5 percentage points at the onset of the peak period and disappear at the end of the peak period.[33]

To summarize how the set points change on average for each pricing period, and to examine whether these changes differ on hotter versus cooler days, we re-estimate Eq. 3 using $Set_{i,p,d}$, household i's average thermostat set point across the intervals during period p (peak, mid-peak, or off-peak) of day d, as the dependent variable. Estimates of the model are made simultaneously for each pricing period using weekday observations from June through September of 2018 and 2019. The top row of Table 2 displays the average changes in the set points across all summer weekdays, again revealing an average increase in peak period set points of 1.04°F. To explore whether these changes differ with the outdoor temperature, we simultaneously estimate the model for each pricing period using three different subsets of days: those with average temperatures in Sacramento below $69°F$, $69°F$ to $75°F$, and

[32]As an additional test for the impact of the TOU rates, we also estimate an alternative specification building on Eq. 1. Instead of focusing exclusively on observations from June through September, we include observations of the 5-minute interval AC usage during May 2018 and May 2019. In addition to the original treatment indicator, $\text{Post}_d \cdot \text{SMUD}_i$, which is 1 for SMUD households in June 2019 and onward, we include an additional treatment indicator, $\text{Pre}_d \cdot \text{SMUD}_i$, which is equal to 1 for SMUD homes during May of 2019. Recall, during May 2019, SMUD households were exposed to a much more mild version of the TOU rates, with only two pricing periods (a peak from 5pm until 8pm and a constant price during all other hours). With the inclusion of the two separate treatment indicators, we are able to estimate how the TOU rates affect AC usage separately in the mild (May) and more severe (June-Sept) TOU regimes. Figure A3 displays the average changes in interval AC usage in the two treatment windows. While there is evidence that the May 2019 TOU rates caused peak period AC usage to decline, there is no evidence of a drop in AC usage at noon during May 2019, consistent with there being no discontinuous price change.

[33]It is worth noting that, while the set point is found to significantly increase in the post-8pm mid-peak intervals, TOU rates in the mid-peak intervals starting at 8pm, the AC usage does not decline. This would be expected if the increase in peak period set points causes the inside of the SMUD homes to increase, resulting in the AC units still operating at the same frequency in the 8pm hour even with the higher mid-peak set points.

above 75°F. The bottom three rows of Table 2 reveal that the pattern in the average set point changes does not meaningfully vary with the outdoor temperature.[34] Ultimately, the fact that the increase in peak period set points does not diminish on the hottest days is consistent with the key finding from Table 1 that largest reductions in AC usage occur on the hottest days. Moreover, the fact that the set point changes do not differ on mild versus hot summer days suggests that the key behavioral response is not day-to-day changes in cooling behavior, but rather permanent changes in households' cooling schedules.

In sum, the preceding results provide evidence that the adoption of default TOU rates led to a significant reduction in peak period AC usage among the SMUD Ecobee households. Moreover, this reduction was the largest on the hottest days, representing roughly a 15% reduction in peak period weekday cooling. To get a sense of how SMUD's total load would be altered by a 15% reduction in peak period residential cooling on the hottest days, it is helpful to return to the bottom left panel of Figure 4. SMUD's lowest average peak period load (1,300 MWh/hour) occurs on days with average temperatures around 60°F and climbs to 2,500 MWh/hour when the daily average temperature exceeds 75°F. This suggests that, on the hottest days, cooling-driven consumption accounts for roughly 50% (1,200 MWh/hour) of SMUD's peak period load. Assuming that half (600 MWh/hour) of this cooling-driven load stems from residential consumers, equal to their share of SMUD's total annual load, and imposing the strong assumption that the 15% decrease in peak period AC use is representative of how the larger population of residential consumers responds to TOU rates, we would predict that the cooling reductions alone caused by the TOU rates result in roughly a 4% (90 MWh) decrease in SMUD's average hourly peak period load on the hottest days.

[34] Column 4 of Table A2 again displays estimates from the augmented version of Eq. 3 that includes the interaction between $\text{Post}_d \cdot \text{SMUD}_i$ and $(\text{Temp}_{i,d} - 64°\text{F})$. Using the average peak period set point as the dependent variable, we again find no evidence that the change in the peak period set point varies with the outdoor temperature.

4 Change in SMUD Load

To directly explore how SMUD's load changes following the introduction of default TOU rates, we first estimate the following simple model using daily observations from 2018 and 2019:

$$\text{Load}_d = \beta \cdot \text{Post}_d + \boldsymbol{\theta} \cdot \mathbf{T}_d + \varepsilon_d, \tag{6}$$

where Load_d represents SMUD's average hourly load (MWh) during the peak, mid-peak, or off-peak hours of day d, and $\mathbf{T}_d$ is the temperature spline specified by Eq. 2.

The top panel of Table 3 displays the point estimates of β from Eq. 6 for the different periods of the day and for different subsets of days.[35] Controlling for the temperature, we find SMUD's average hourly peak period load fell by 187 MWh on summer weekdays in 2019 relative to 2018. Concluding that this reduction reflects the causal impact of the TOU rates would require imposing the untenable assumption that, aside from the temperatures and the retail rates, no other determinants of load systematically change across years. Indeed, Table 3 displays strong evidence that SMUD's load fell for reasons beyond the adoption of the TOU rates. Notably, there are consistent declines of 40 to 65 MWh in the average hourly peak period load on summer weekends and non-summer weekdays. Moreover, very similar (40 to 50 MWh) declines in the average hourly load occur during the off-peak hours and the mid-peak hours outside of summer weekdays. These stable reductions in load outside of the periods when the TOU rates increased the per kWh price are consistent with SMUD's load falling due to factors that are likely exogenous to the TOU program.[36]

As an alternative way to test whether the TOU rates alter SMUD's load, we examine how the daily peak to mid-peak spread – i.e. the within-day difference between the average hourly peak period load and the average hourly mid-peak load – changes from 2018 to 2019. Intuitively, if the increase in the peak period price reduces peak period load, we would expect

[35] The reported standard errors are robust to clustering at the week-of-sample level.

[36] These reductions in load are consistent with evidence from Davis et al. (2017) demonstrating steady declines in residential electricity use.

to see the peak to mid-peak spread decrease following the adoption of the TOU rates. The lower panel of Table 3 displays the estimates of Eq. 6 using the daily peak to mid-peak spread as the dependent variable.[37] After controlling for temperature differences, we find the average daily peak to mid-peak spread falls by 73 MWh during summer weekdays in 2019 relative to 2018.

An advantage of focusing on the within-day peak to mid-peak spread is that any load changes caused by exogenous, non-TOU driven factors that uniformly reduce SMUD's load across periods of the day (e.g., increases in the energy efficiency of baseload appliances like refrigerators) will be differenced away. However, if changes in SMUD's load are caused by non-TOU factors that affect load differently across periods of the day, then simply focusing on the peak to mid-peak spread will not difference away these potentially confounding factors. For example, reductions in the demand for cooling or efficiency improvements in insulation, AC units, or lighting would all be expected to cause load to fall more during the peak period compared to the mid-peak period. Consequently, if any of these non-TOU changes are occuring between 2018 and 2019, we would expect to see the peak to mid-peak spread decline. Of course, if any of these non-TOU factors are responsible for the 73 MWh drop in the peak to mid-peak spread on summer weekdays, they would also be expected to cause similar declines during summer weekends, or potentially non-summer weekdays. However, Table 3 highlights that there are no significant changes in the peak to mid-peak spread outside of summer weekdays.

While the reduction in the peak to mid-peak spread on summer weekdays provides strong evidence that SMUD's peak period load has fallen in response to the default TOU rates, it is important to note that the 73 MWh decrease could theoretically over or understate the causal effect of TOU rates on SMUD's peak load. Recall, the default TOU plan not only increased the peak period price, it also increased the mid-peak price, albeit by a far smaller amount. On the one hand, the within-day variation in prices could incentivize households

[37]Note, the resulting estimate of β is equivalent to the difference between the point estimates of β found using the average peak period load and the average mid-peak period loads as the dependent variables.

to shift some of their peak period consumption to the mid-peak hours (i.e. load shifting). On the other hand, the increase in mid-peak prices provides an incentive to reduce mid-peak consumption.[38] If the load-shifting effect dominates, and mid-peak period consumption increases in response to the TOU rates, then the 73 MWh decrease in the peak to mid-peak spread will overstate the reduction in peak period load. In contrast, if households reduce mid-peak consumption in response to the TOU rates, the 73 MWh decrease will understate the average peak period energy savings.

Returning to the estimates displayed in Table 3, the evidence suggests that mid-peak loads falls in response to the TOU rates. Notably, the average hourly mid-peak load fell by far more on summer weekdays compared to summer weekends and non-summer weekdays.[39] As a result, we view the 73 MWh decrease in the peak to mid-spread as a lower bound on the average hourly peak period savings caused by the default TOU rates. Given that there is no evidence of the off-peak period load changing in response to the default TOU rates – the average hourly off-peak load falls by nearly the same amount on summer weekdays, summer weekends, and non-summer weekends – a less conservative estimate of the peak period savings can be made by instead focusing on how the daily peak to off-peak spread changes. Re-estimating Eq. 6 using the daily peak to off-peak spread as the dependent variable, we find an average decrease of 146 MWh on summer weekdays (Table 3). Again, there is no change in this peak to off-peak spread outside of the summer weekdays.

The preceding results provide evidence that adopting default residential TOU rates caused SMUD's average hourly peak period load to fall by at least 73 MWh, and likely more in the range of 146 MWh, on summer weekdays. To quantify the role that reductions in cooling play, we estimate how the peak to mid-peak spread reductions differ with the daily temperature. Consistent with the TOU rates reducing peak period AC use, we estimate that

[38]Moreover, the peak period price increase could cause consumption reductions that spillover to the surrounding mid-peak hours. For example, households with non-programmable thermostats may permanently set their thermostats to a higher temperature, reducing AC runtimes across all afternoon hours.

[39]Similarly, the average daily spread between the mid-peak and off-peak load only falls on summer weekdays (bottom row of Table 3).

the average reduction in the peak to mid-peak spread grows from 41 MWh on days with average temperatures below $69°F$ to 104 MWh on days with average temperatures $75°F$ or above (Table 3).[40]

Attributing this difference in energy savings across hotter and cooler days to the TOU-induced reductions in cooling, we conservatively estimate that, on weekdays with average temperatures $75°F$ or above, the amount of energy used for cooling fell by $104 - 41 = 63$ MWh per hour during the peak period. Examining instead the less conservative peak to off-peak spread measure, we find the peak to off-peak spread falls by 104 MWh on summer weekdays with average temperatures below $69°F$ and by 210 MWh on days with average temperatures of $75°F$ or above.[41] This suggests that, on the hottest weekdays, the TOU-induced reductions in residential cooling have cut SMUD's hourly peak period loads by over 100 MWh, roughly a 4 to 5% reduction.

It is important to note that, since SMUD's adoption of default TOU rates, California's electricity market has experienced steady growth in solar capacity. As supply from solar has continued to grow during the daylight hours, the peak net-demand (aggregate demand for electricity minus solar output), and consequently the peak wholesale energy prices, have steadily moved from the 6-8pm window observed during 2019 (see Figure 1) to slightly later (7-9pm in more recent years).[42] Consequently, many of the default TOU rate structures that have since been adopted by the state's Investor Owned Utilities (e.g., PG&E) now include peak price periods that begin at 4pm and extend out to 9pm. Given that demand for cooling in the Central Valley remains high through 9pm in the summer months (see the top panel of Figure 2), our results suggest that the longer peak price window will still achieve peak period AC savings. However, given that our results reveal that the energy savings begin to diminish in the later portion of SMUD's peak price period (see Figure 2), this suggests that

[40] If non-TOU factors (e.g. reductions in AC demand) cause larger reductions on hotter days, we would expect to see the same pattern emerge on summer weekends, which we do not observe (see Figure A4).

[41] See Table A3 for the estimates.

[42] Bushnell and Novan (2021) present evidence of wholesale prices shifting later in the evening with the expansion in solar capacity.

the 4pm to 9pm TOU rates may be reducing a slightly smaller percentage of load during the 7pm to 9pm period when the net-demand on the grid peaks.[43]

5 Conclusion

To incentivize consumers to reduce electricity consumption when the marginal cost is high, economists have long advocated for time-varying prices, the simplest form being TOU rates. By 2019, nearly half of US investor owned electric utilities were offering their residential customers the option to enroll in TOU programs. However, in locations where residential TOU programs are available, an average of only 3 percent of households were enrolled as of 2019 (Faruqui, Hledik and Sergici, 2019). This has begun to change. Notably, by the end of 2022, the majority of California households were facing default TOU rates.

A common concern with TOU rates is that they do not provide relatively stronger signals to reduce consumption on higher demand days. Indeed, the importance of reducing consumption on the highest demand days is only expected to increase with extreme temperatures becoming more common and peak system demands continuing to grow (Auffhammer, Baylis and Hausman, 2017). While greater efficiency gains could be achieved by adopting prices that vary with the marginal cost across days (e.g., Borenstein (2005)), our results reveal that, even without varying the price signal across days, simple TOU rates can induce sizable reductions in peak period cooling, and thus achieve peak period energy savings that are concentrated on the highest demand days.

While our empirical analysis focuses narrowly on the impacts of a TOU program adopted in Sacramento, CA, our findings are nonetheless relevant far more broadly. For example, throughout much of the US, the timing of the system peaks on regional electric grids is driven

[43]It is also possible that decay in energy savings during the 7pm to 8pm window under SMUD's 2019 TOU rates (see Figure 2 and 3) were in part due to the fact that, as AC usage was reduced at the onset of the peak price window (at 5pm), the SMUD households became steadily warmer as the peak period progressed, resulting in AC units operating relatively more frequently later in the peak price window as opposed to earlier in the peak price window. Given this dynamic pattern to the energy savings, it may be beneficial for future work to examine whether a later start to the peak price period (i.e. later than 4pm) could result in greater sustained energy savings out through the 8pm to 9pm window when the peak wholesale prices now occur.

by demand for temperature control, and in particular, cooling (Auffhammer, Baylis and Hausman, 2017). While programmable thermostats are commonplace in US households – as of 2020, 62% of single-family homes in the US had a programmable thermostat – adoption of TOU rate programs remains low.[44] Our results suggest that, by inducing households to alter their regular summer cooling schedules, simple TOU rate structures can play an important role in reducing the peak system demands, and thus provide large cost savings.

[44]The US EIA RECS data (Table HC7.1) estimates that 61.% of single-family detached or attached housing units had a programmable or smart (or internet-connected) thermostat in the 2020 survey wave.

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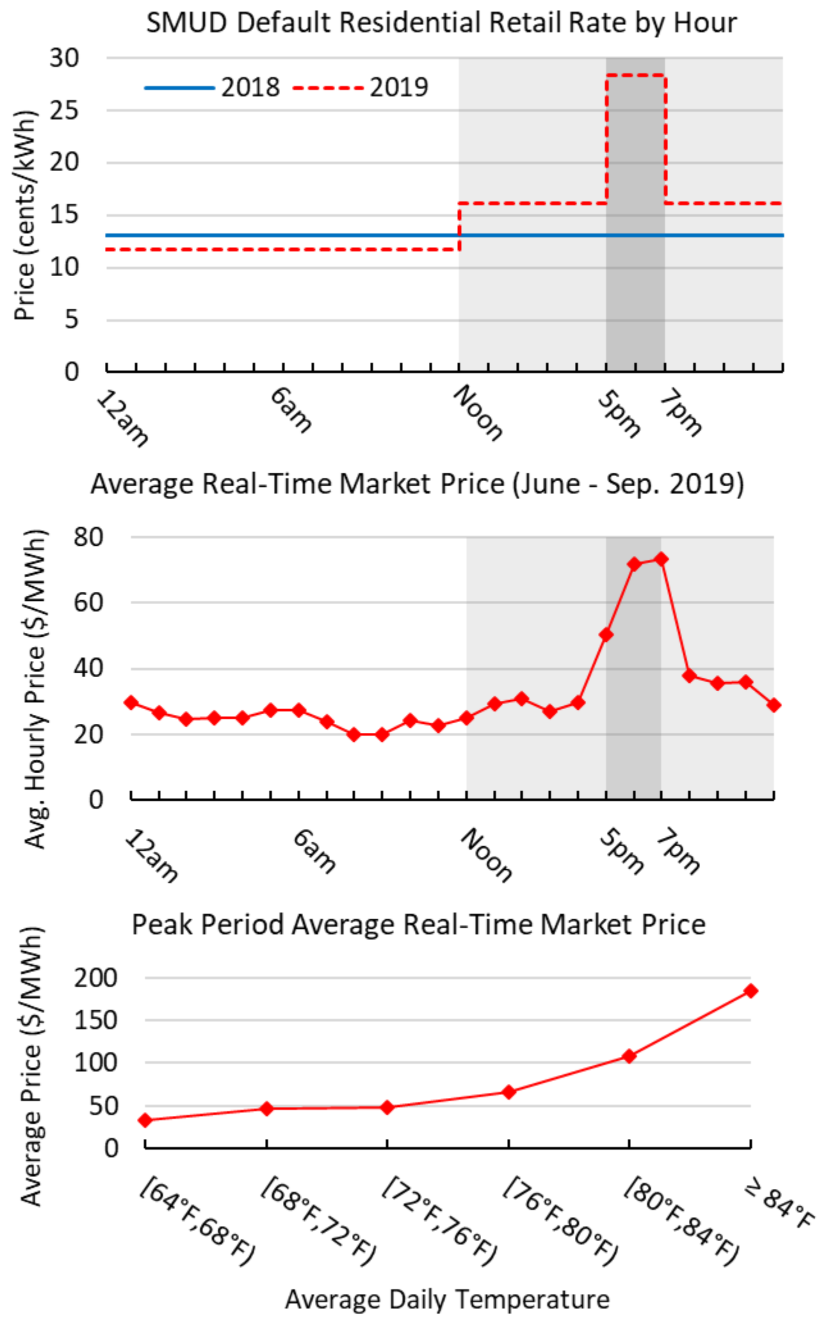


Figure 1: The top panel displays the default residential volumetric charge (cents/kWh) for SMUD customers on non-holiday weekdays during Summer (June 1 through September 30) 2018 and 2019. The middle panel displays the average 5-minute interval CAISO Real-Time Market (RTM) price ($/MWh) by hour of day for June through September of 2019. The prices are recorded for the NP-15, Northern California Congestion Management Zone, which encompasses SMUD's service territory. The bottom panel displays the average 5-minute interval RTM price, conditional on the daily average temperature, during the peak-price period (5pm until 8pm) over days spanning June through September 2019.

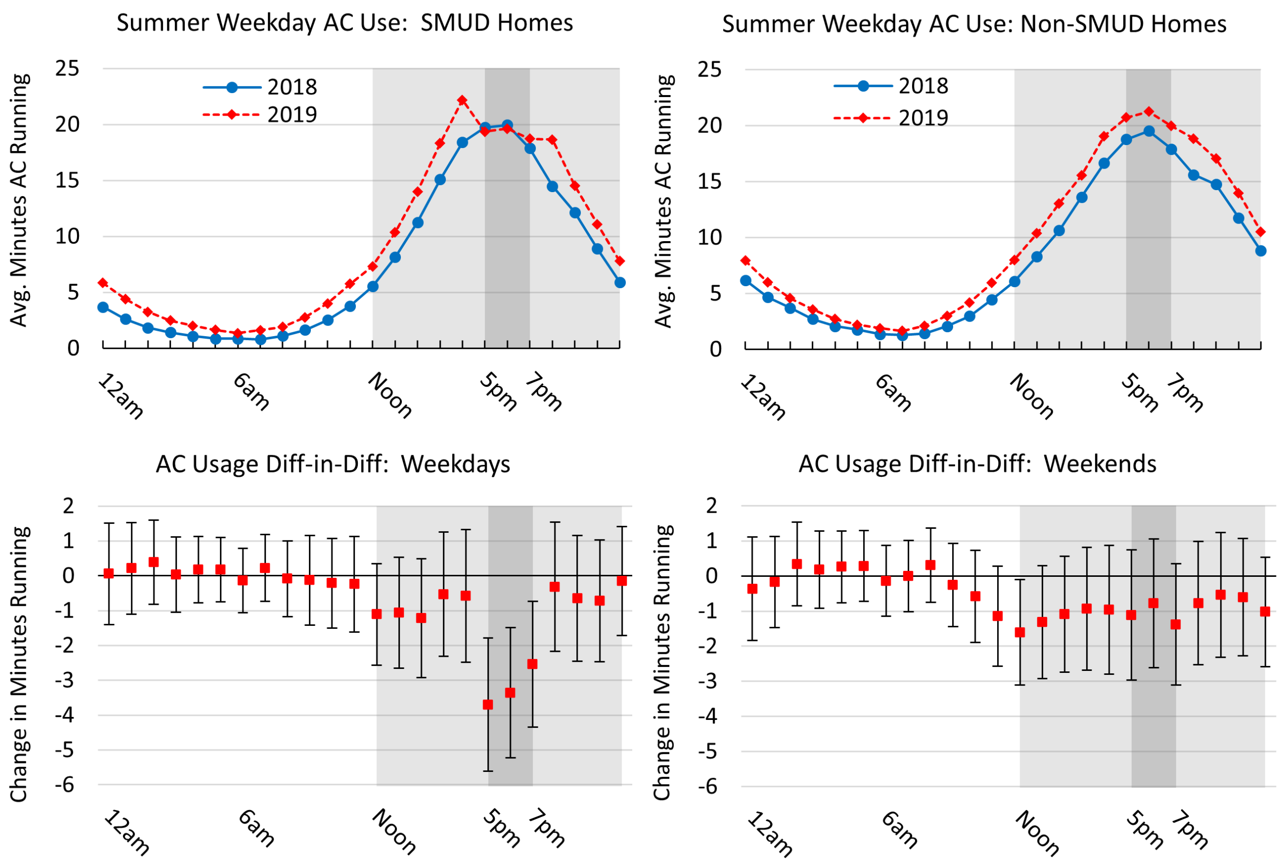
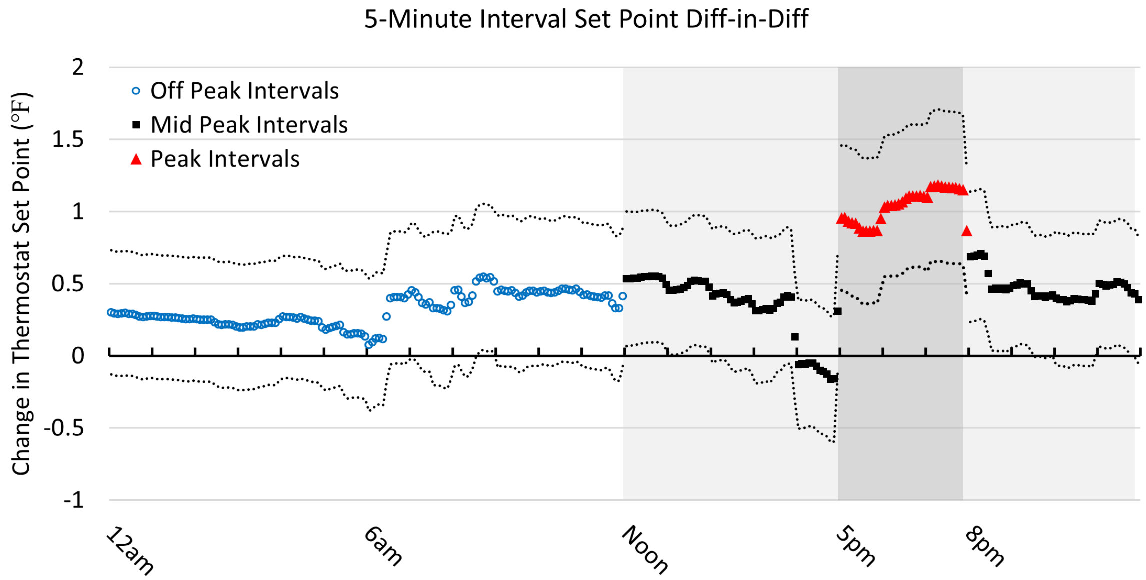


Figure 2: The top panels display the average minutes per hour AC units are running during summer (June through September) weekdays among the homes observed in the SMUD (left) and non-SMUD (right) service territories. The light shaded area represents the mid-peak hours. The darker shaded area represents the peak hours. The bottom row displays estimates of β_h from Eq. 1, and the corresponding 95% confidence intervals which are robust to clustering at the household-level, for summer weekdays (left) and summer weekends (right).



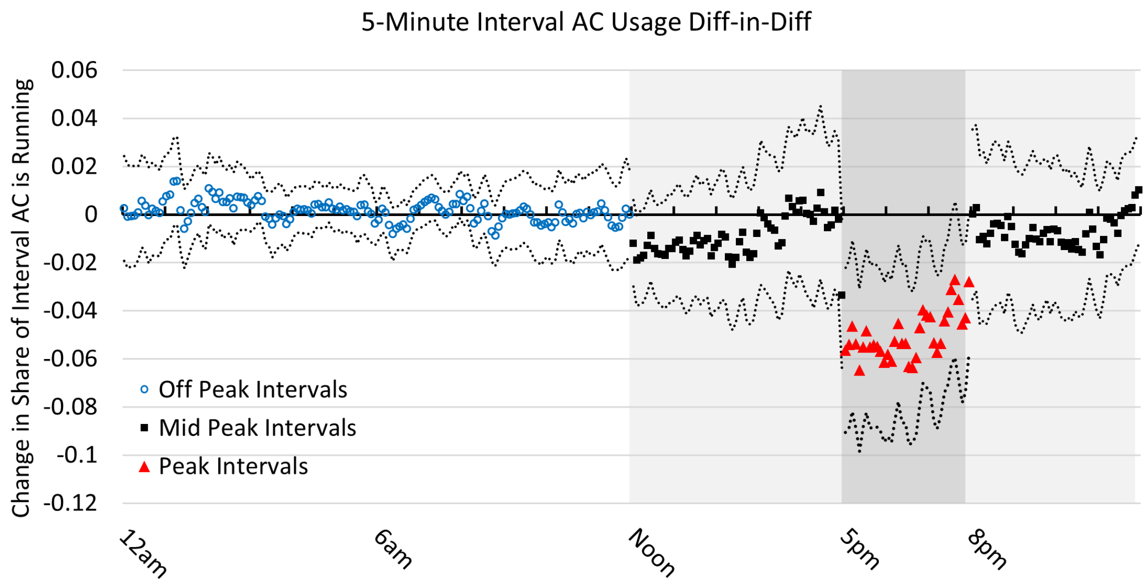


Figure 3: The top panel displays estimates of β_t, the average change in 5-minute interval thermostat set points (°F) from Eq. 5 and the corresponding 95% confidence intervals, which are robust to clustering at the household-level, for summer weekdays. The light shaded area represents the mid-peak intervals. The darker shaded area represents the peak intervals. The bottom panel displays the estimates of β_t from Eq. 5 (and the corresponding 95% confidence intervals) using the 5-minute interval AC runtime (measured as the share of the interval the AC is running) as the dependent variable.

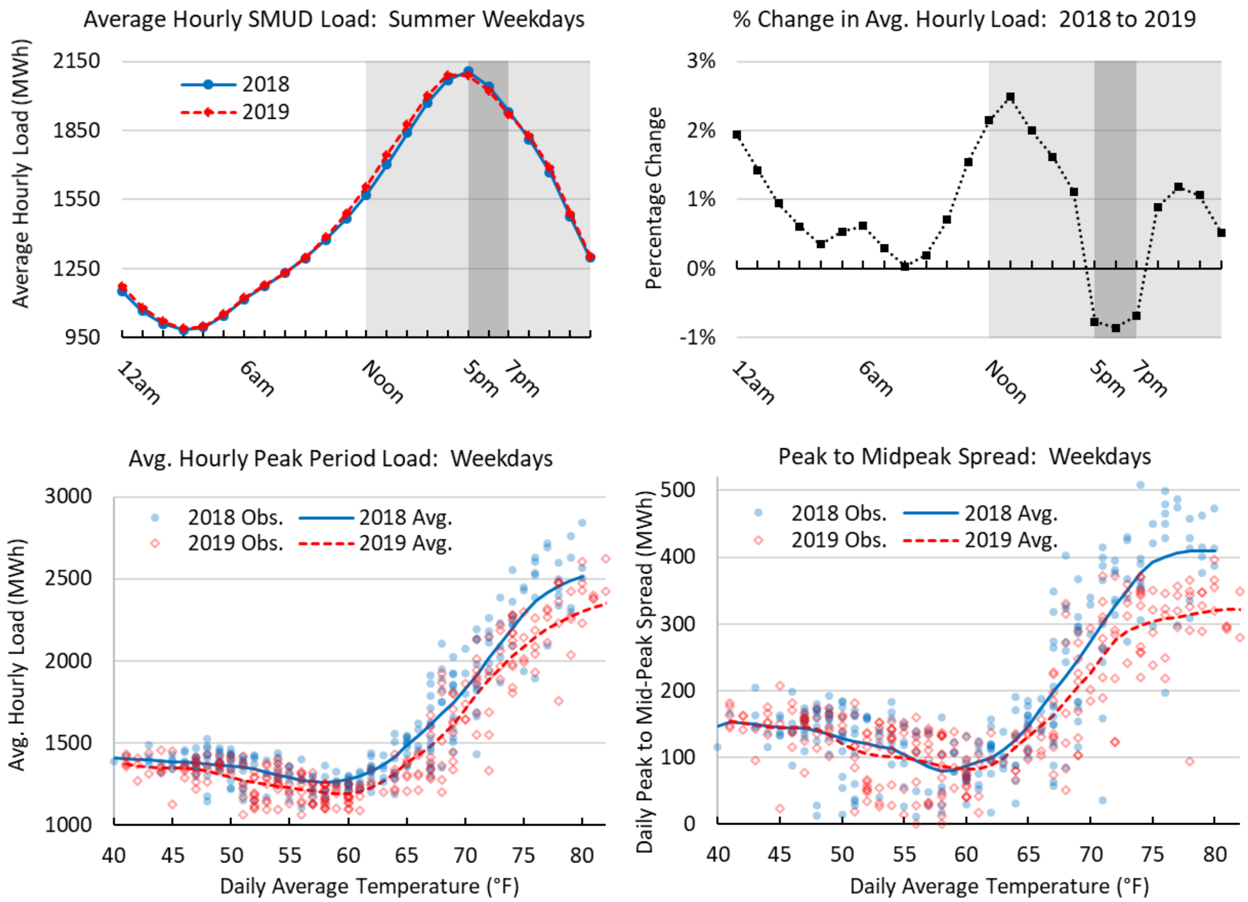


Figure 4: The top left panel displays the average hourly aggregate SMUD load on summer weekdays during 2018 and 2019. The top right panel displays the percentage changes in the average hourly summer weekday load from 2018 to 2019. The bottom left panel displays a scatter plot of the observed average hourly SMUD load during the peak period (5pm until 8pm) for each summer weekday during 2018 and 2019 against the daily average temperature. The solid and dashed lines display kernel weighted, local polynomial smoothed averages of the hourly peak period load conditional on the daily average temperature. The conditional averages were calculated using Epanechnikov kernel weights with a $2°F$ bandwidth. The lower right panel displays the observed, and local polynomial smoothed averages, of the daily peak to mid-peak spread – the difference between the daily average hourly load during the peak period and the daily average hourly load during the mid-peak period – for Summer weekdays during 2018 and 2019.

Table 1: Change in AC Running Time (minutes per hour)

	Diff-in-Diff		SMUD		Non-SMUD	
Period of Day	Weekday (T=162)	Weekend (T=64)	Weekday (T=162)	Weekend (T=64)	Weekday (T=162)	Weekend (T=64)
Peak Hours						
All Days	-3.20**	-1.10	-3.46**	0.58	-0.03	1.47**
	(0.79)	(0.74)	(0.66)	(0.60)	(0.42)	(0.44)
$Temp \geq 75°$ (T=49 days)	-4.50**		-4.03**		-0.31	
	(1.05)		(0.87)		(0.67)	
$69° \leq Temp < 75°$ (T=73 days)	-3.35**		-4.31**		-0.58	
	(0.85)		(0.74)		(0.43)	
$Temp < 69°$ (T=40 days)	-1.67**		-1.80**		0.35	
	(0.59)		(0.50)		(0.35)	
Mid-Peak Hours	-0.70	-0.99*	-0.04	0.60	0.79**	1.42**
	(0.48)	(0.49)	(0.40)	(0.40)	(0.27)	(0.28)
Off-Peak Hours	0.04	-0.11	0.40	0.24	0.40**	0.33*
	(0.24)	(0.25)	(0.21)	(0.20)	(0.12)	(0.16)
Number of Households	287	287	132	132	155	155
Premise-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Sample FE	Yes	Yes	No	No	No	No

The first two columns display estimates of β_p from Eq. 3. This parameter represents the average change, from 2018 to 2019, in the minutes per hour a SMUD household's AC unit is operating during the specific period (the peak hours (5pm-8pm), the mid-peak hours (noon-5pm and 8pm-midnight), or the off-peak hours (midnight to noon)) on weekdays or weekends during the summer months (June through September). Each of the models for Columns 1 and 2 are estimated using a spline of the average daily temperatures with knots at $70°F$ and $75°F$ as well as household-by-month fixed effects and day-of-sample fixed effects. Columns 3 through 6 display estimates of the average change in AC runtimes from 2018 to 2019 for the SMUD or non-SMUD households separately (Eq. 4). Each model includes the temperature spline as well as premise-by-month fixed effects. The models identifying the average runtime change across each of the three daily periods, on weekdays and weekends, are estimated simultaneously. Columns 1, 3, and 5 also display estimates of β_p for the peak period, restricting the sample to summer weekdays with average temperatures in specific ranges. The number of days (T) included in each subset of the data is listed at the top of each column (unless noted otherwise in the specific row of results). The standard errors, reported in parentheses, are robust to clustering at the household level. * = significant at the 5% level; ** = significant at the 1% level.

Table 2: Change in Thermostat Set Point (°F)

	Peak Hours	Mid-Peak Hours	Off-Peak Hours
All Days	1.04^{**}	0.40^{*}	0.31
(T=162 days)	(0.24)	(0.18)	(0.19)
Temp $\geq 75°$	1.00^{**}	0.36	0.22
(T=49 days)	(0.26)	(0.20)	(0.20)
$69° \leq$ *Temp* $< 75°$	1.14^{**}	0.48^{*}	0.37^{**}
(T=73 days)	(0.28)	(0.21)	(0.22)
Temp $< 69°$	1.04^{**}	0.39	0.35
(T=40 days)	(0.29)	(0.22)	(0.23)
Premise-by-month FE	Yes	Yes	Yes
Day-of-Sample FE	Yes	Yes	No

The first row displays estimates of the average change, from 2018 to 2019, in the SMUD households' thermostat set points (measured in °F) – β_p from Eq. 3 using the average thermostat set points as the dependent variable. Each of the period-specific models are estimated using a spline of the average daily temperatures with knots at $70°F$ and $75°F$ as well as household-by-month fixed effects and day-of-sample fixed effects. The models identifying the average set point change across each of the three daily periods are estimated simultaneously. Rows two through four display estimates of the average set point changes restricting the sample to summer weekdays with average temperatures in specific ranges. The number of days (T) included in each subset of the data is listed in column 1. The models for each period of the day, and for each temperature subset, are estimated simultaneously. The standard errors, reported in parentheses, are robust to clustering at the household level. * = significant at the 5% level; ** = significant at the 1% level.

Table 3: Change in Peak Load and Peak to Non-Peak Spreads

Dependent Variable	Summer Weekdays (T=172)	Summer Weekends (T=72)	Non-Summer Weekdays (T=350)
Average Hourly Peak Period Load (MWh)			
All Days	-186.9**	-61.3	-65.2**
	(39.5)	(45.6)	(19.0)
Daily Temp $\geq 75°F$ (T=58)	-256.3**		
	(61.2)		
$69°F \leq$ *Daily Temp* $< 75°F$ (T=73)	-154.1**		
	(45.9)		
Daily Temp $< 69°F$ (T=41)	-149.3*		
	(69.1)		
Average Hourly Mid-Peak Period Load (MWh)	-113.5**	-52.0	-62.3**
	(27.8)	(32.2)	(10.9)
Average Hourly Off-Peak Period Load (MWh)	-40.7**	-43.9**	-45.5**
	(8.7)	(12.1)	(15.9)
Peak to Mid-Peak Spread (MWh)			
All Days	-73.4**	-9.3	-2.9
	(12.6)	(15.3)	(9.7)
Daily Temp $\geq 75°F$ (T=58)	-104.2**		
	(16.8)		
$69°F \leq$ *Daily Temp* $< 75°F$ (T=73)	-66.2**		
	(15.2)		
Daily Temp $< 69°F$ (T=41)	-40.5		
	(26.6)		
Peak to Off-Peak Spread (MWh)	-146.1**	-17.4	-19.8
	(34.1)	(39.0)	(12.7)
Mid-Peak to Off-Peak Spread (MWh)	-72.8**	-8.1	-16.9
	(22.1)	(25.4)	(10.8)

Each element in the table is an estimate of β in Eq. 6. This parameter represents the average change, from 2018 to 2019, in SMUD hourly load (measured in MWh), or in the within-day spread in SMUD hourly load. The number of days (T) included in each subset of the data is listed at the top of each column (unless noted otherwise in the specific row of results). Each of the models are estimated using a spline of the average daily temperatures with knots at $70°F$ and $75°F$. The standard errors, reported in parentheses, are robust to clustering at the weekly level. * = significant at the 5% level; ** = significant at the 1% level.

Online Appendix

A Non-SMUD Ecobee Sample Construction

When constructing the non-SMUD sample from the Ecobee DYD dataset, our objective was to restrict the sample to households residing in the northern portion of California's Central Valley, the same region where Sacramento is located. Doing so ensures that the summer climates experienced by the households would be largely similar to the SMUD households. To do so, we utilized the California Energy Commission's (CEC) county-level Climate Zone designations (see https://www.energy.ca.gov/files/building-climate-zones-map). The CEC classifies counties based on their typical heating and cooling degree patterns. These Climate Zone designations are then used for a variety of purposes (e.g., building energy efficiency standards differ across Climate Zones). Sacramento County falls in Climate Zone 12, the central portion of the Central Valley. While slightly warmer, Climate Zone 13, which is the southern portion of the Central Valley, has similar climate patterns to Climate Zone 12. Ultimately, we restrict our non-SMUD sample to include households in Climate Zones 12 and 13. In addition to restricting the set of counties, we restricted the sample to only include households with a full time-series of observations from May 2018 through September 2019.

The final non-SMUD sample consists of 155 households. For each of these households, we calculate the average daily temperature for each summer day during 2018 and 2019 using the nearest NOAA weather station with an uninterrupted time series of . The cities represented in the final non-SMUD sample (and the location of the NOAA weather station used for each group of cities) include (Stockton Metropolitan Airport weather station for the following) Lodi, Tracey, Manteca, Lathrop, (Fresno Executive Field weather station for the following cities) Fresno, Selma, Clovis, Sanger, Reedley, Kingsburg, (Merced Regional Airport weather station for the following) Merced, Oakdale, Riverbank, Atwater, Livingston, Delhi, (Madera Municipal Airport weather station for the following) Chowchilla, (Modesto City-County Airport weather station for the following) Salida, Ripon, Turlock, Ceres, (Sacramento International Airport weather station for the following) Roseville, Davis, West Sacramento.

Table A1: SMUD and Non-SMUD Household Summary Statistics

	SMUD Households		Non-SMUD Households	
	2018	2019	2018	2019
Avg. AC Runtime (minutes per hour)				
All Hours	7.79	8.92	9.01	9.46
Peak Hours	19.38	19.41	18.71	19.62
Mid-Peak Hours	11.56	13.42	12.98	13.82
Off-Peak Hours	2.06	2.95	3.60	3.64
Avg. Thermostat Set Point (°F)				
All Hours	77.77	77.77	78.01	77.56
Peak Hours	77.63	78.36	77.82	77.50
Mid-Peak Hours	77.82	77.77	78.01	77.56
Off-Peak Hours	77.76	77.60	78.02	77.54
Daily Average Temperatures (°F)				
Mean	72.0	73.5	76.0	76.9
Maximum	84	86	92	93
Minimum	62	58	62	57
Number of Households	132		155	
Share Detached Homes	0.71		0.72	
Avg. Home Age (years)	30.2		20.2	
Avg. Square Footage	2,343		2,494	
Avg. Number of Floors	1.61		1.62	
Avg. Number of Occupants	3.16		2.85	
Avg. Ecobee Connection Year	2016		2016	

The top four rows display the average AC runtime on weekdays during the summer months (June through September) of 2018 and 2019 for the SMUD and non-SMUD households in our Ecobee's dataset. The next four rows display the average thermostat set points (^{c}ircF). The daily average temperature for the SMUD homes is recorded at the Sacramento International Airport NOAA weather station. For each non-SMUD household, the daily average temperature at the nearest NOAA weather station (described in Appendix A) is used. Finally, the last six rows display the share of the SMUD and non-SMUD households that reside in detached premises (the rest being a combination of town/row houses, and condominiums) and the simple average of the self-reported home age, square footage, number of floors, number of occupants, and first year owning the Ecobee thermostat for a subset of the SMUD and Non-SMUD sample. For each of these five variables, a varying number of SMUD and non-SMUD households do not report the given value in the DYD dataset.

Table A2: Heterogeneity in Peak Period Impacts

Independent Variable	Dependent Variable: Runtime (mins/hour)	ln(Runtime)	ln(Runtime)	Set Point
$\text{Post}_d \cdot \text{SMUD}_i$	-1.01	-0.237**	-0.114	1.17**
	(0.74)	(0.063)	(0.076)	(0.24))
$(\text{Post}_d \cdot \text{SMUD}_i) \cdot (Temp_{i,d} - 64)$	-0.26**		-0.014*	-0.015
	(0.09)		(0.006)	(0.012)

The second column displays the estimate of β_p from Eq. 3 using the natural log of the daily average peak period runtime (measure in minutes per hour) on June through September weekdays as the dependent variable. Columns 1, 3, and 4 present three sets of estimates, using alternative dependent variables, from an augmented version of Eq. 3 that includes the interaction between the daily average temperature ($Temp_d - 64$°F) and the treatment variable (Post$_d$·SMUDi). Each of the models include a spline of the average daily temperatures with knots at $70°F$ and $75°F$ as well as household-by-month fixed effects and day-of-sample fixed effects. The standard errors, reported in parentheses, are robust to clustering at the household level. * = significant at the 5% level; ** = significant at the 1% level.

Table A3: Change in Summer Weekday Peak to Off-Peak Spread

	$\text{Temp}_d < 69°F$	$69 \leq \text{Temp}_d < 75°F$	$\text{Temp}_d \geq 75°F$
Peak to Off-Peak Spread (MWh)	-104.4	-118.2**	-209.6**
	(67.0)	(40.4)	(50.7)
	$T = 41$	$T = 73$	$T = 58$

Each element in the table is an estimate of β in Eq. 6. This parameter represents the average change, from 2018 to 2019, in the peak to off-peak spread (the average hourly load during the peak hours of a day minus the average hourly load during the off-peak hours of the day). The table displays the average change in the AC runtime on summer weekdays when the daily average temperature at the Sacramento Airport is greater than or equal to $75°F$, between $69°F$ and $75°F$, and less than $69°F$. The number of days (T) included in each subset of the data is listed at the bottom of each column. Each of the models are estimated using a spline of the average daily temperatures with knots at $70°F$ and $75°F$. The standard errors, reported in parentheses, are robust to clustering at the weekly level. * = significant at the 5% level; ** = significant at the 1% level.

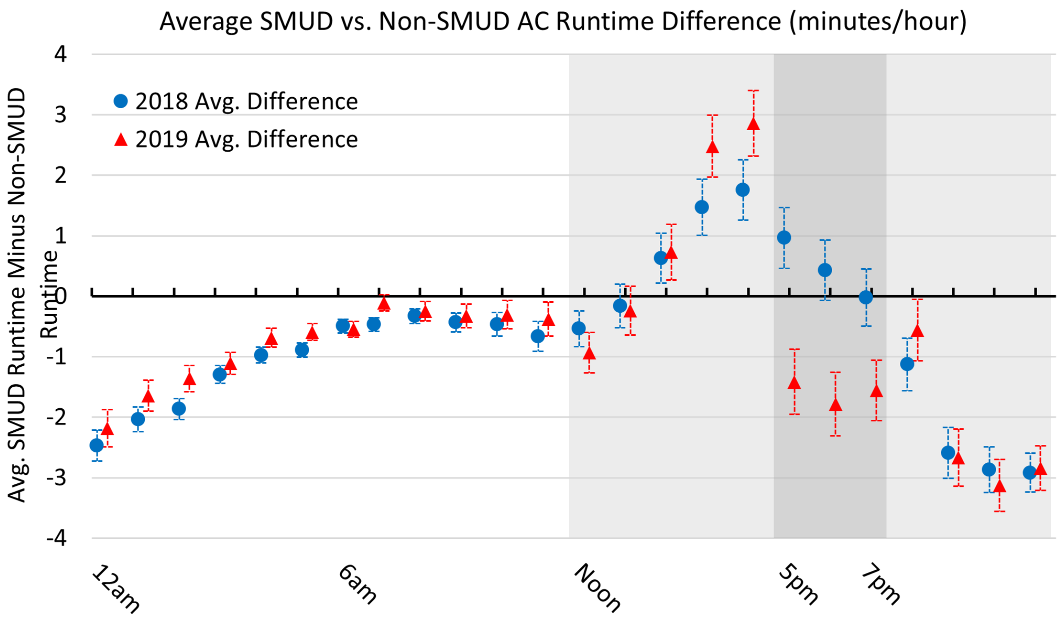


Figure A1: The values displayed in the figure represent difference across the average hourly AC runtime (in minutes per hour) in SMUD and non-SMUD hosueholds. The differences in means across the two samples are calculated separately for each hour of the day in 2018 and again in 2019 using observations from summer (June through September) weekdays. The 95% confidence interval surrounding each simple difference in means is also displayed. The light gray area represents the hours in which SMUD households faced mid-peak prices during summer 2019. The darker gray area represents the hours in which the SMUD households faced peak period prices during summer 2019.

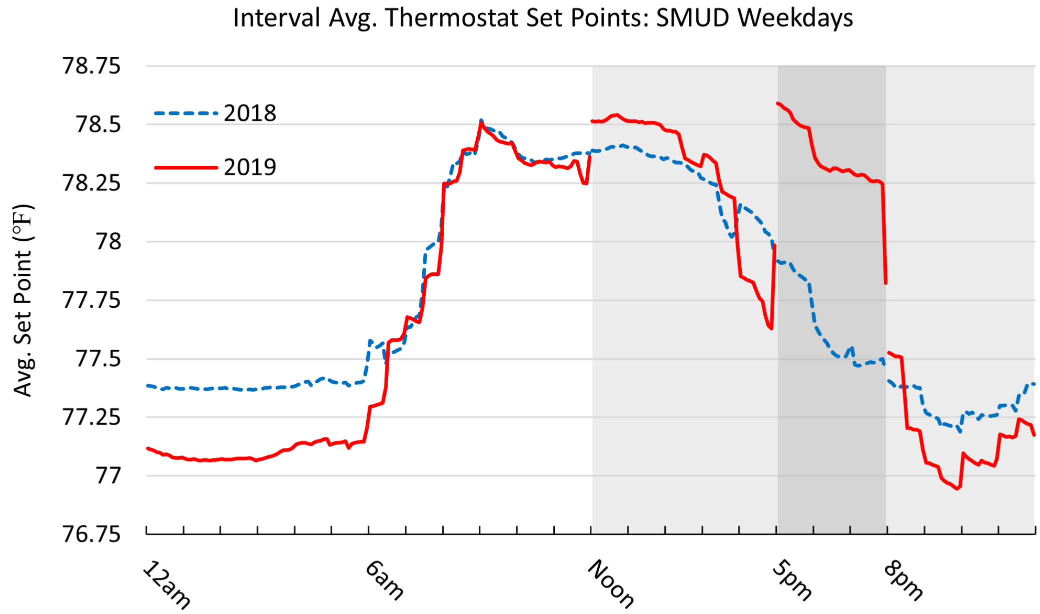


Figure A2: The figure displays the average 5-minute interval thermostat set points among the SMUD hosueholds on summer (June through September) weekdays during 2018 and 2019. The light gray area represents the intervals in which SMUD households faced mid-peak prices during summer 2019. The darker gray area represents the hours in which the SMUD households faced peak period prices during summer 2019.

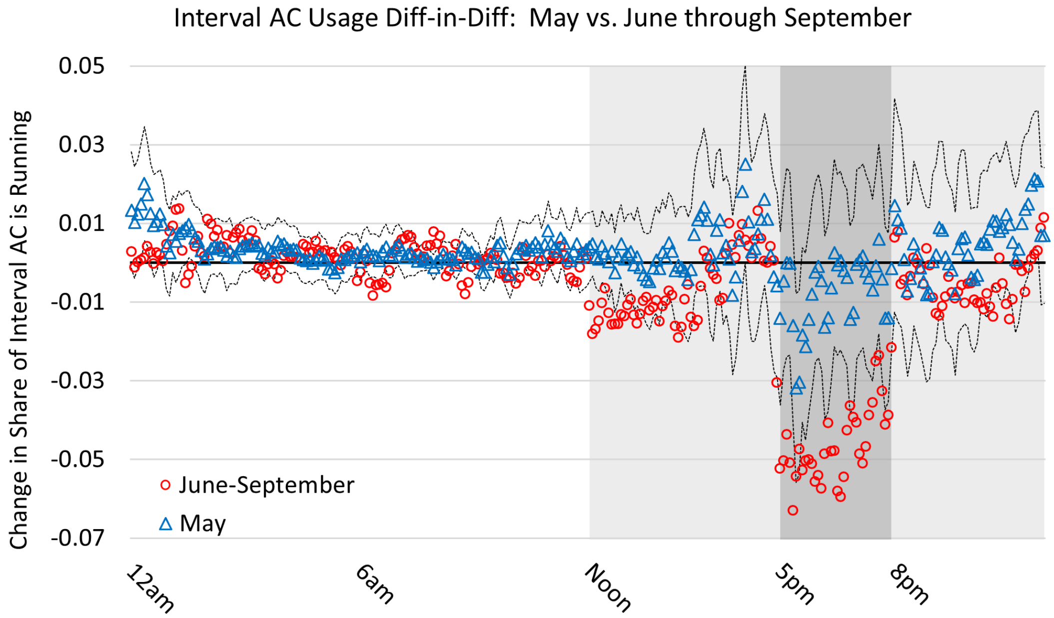


Figure A3: The figure displays estimates from an augmented version of Eq. 5. We again use the 5-minute interval AC runtime (measured as the share of the interval the AC is running) as the dependent variable. In contrast to the primary specification which is estimated using observations from June through September of 2018 and 2019, we now include observations from May 2018 and May 2019. To allow the average impact of the TOU rates to differ in May 2019 relative to June-September 2019, we include two binary treatment indicator variables in the augmented model. In the right hand side of the model, we now include $\text{Pre}_d{\cdot}\text{SMUD}_i$, which is equal to 1 for SMUD households during May 2019, and $\text{Post}_d{\cdot}\text{SMUD}_i$, which equals 1 for observations from SMUD households during June through September of 2019. The triangles display the point estimates for the average change in the 5-minute interval AC runtimes during May 2019 (with the corresponding 95% confidence interval which is robust to clustering at the household level). The circles display the point estimates of the average change in interval AC runtimes during June through September of 2019. The light gray area represents the intervals in which SMUD households faced mid-peak prices during summer 2019. The darker gray area represents the hours in which the SMUD households faced peak period prices during summer 2019.

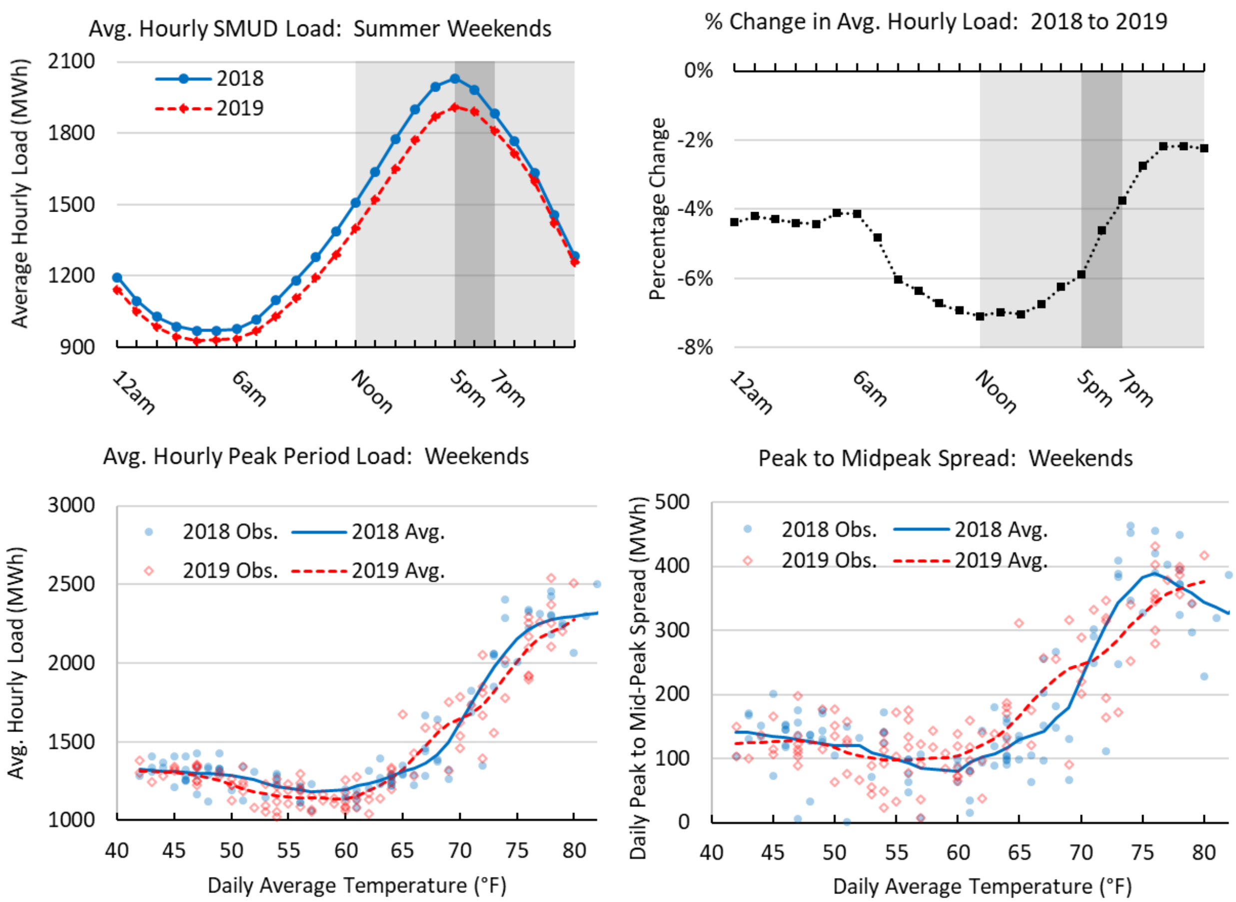


Figure A4: The top left panel displays the average hourly aggregate SMUD load on summer weekends during 2018 and 2019. The top right panel displays the percentage changes in the average hourly summer weekend load from 2018 to 2019. The bottom left panel displays a scatter plot of the observed average hourly SMUD load during the peak period (5pm until 8pm) for each summer weekend day during 2018 and 2019 against the daily average temperature. The solid and dashed lines display kernel weighted, local polynomial smoothed averages of the hourly peak period load conditional on the daily average temperature. The conditional averages were calculated using epanechnikov kernel weights with a $2°F$ bandwidth. The lower right panel displays the observed, and local polynomial smoothed averages, of the daily peak to mid-peak spread – the difference between the daily average hourly load during the peak period and the daily average hourly load during the mid-peak period – for summer weekends during 2018 and 2019.

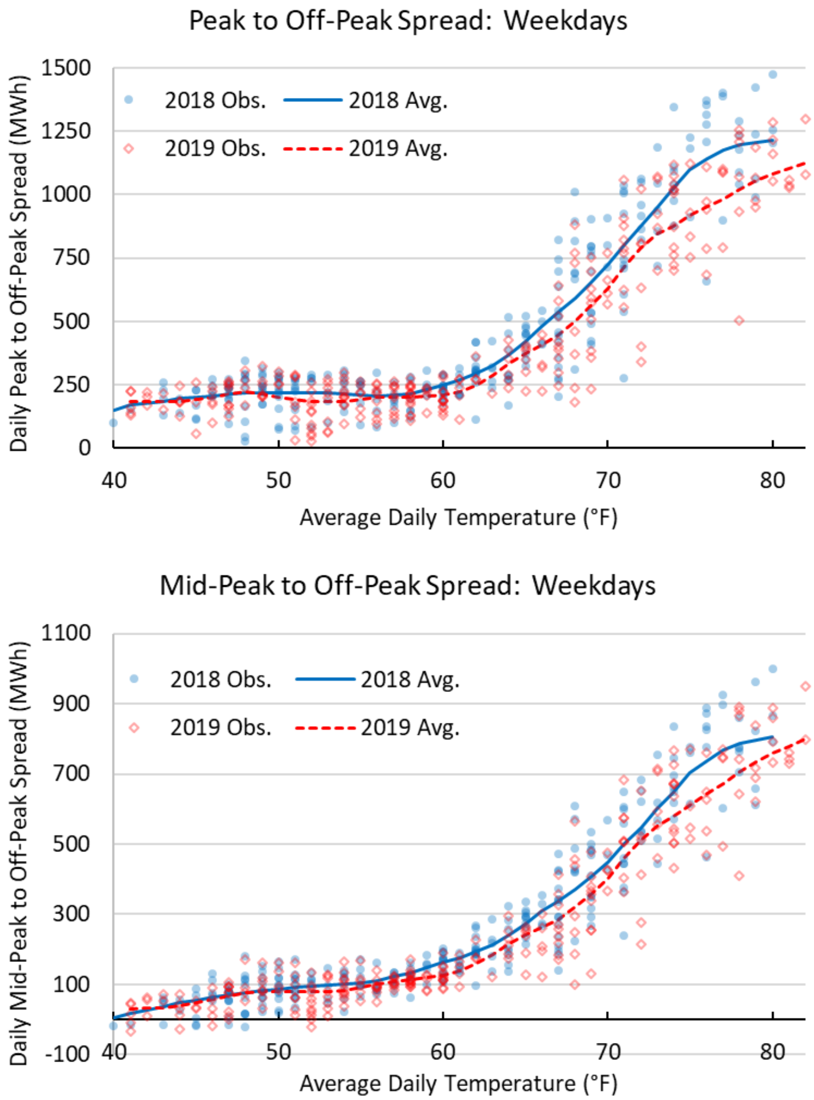


Figure A5: The top panel displays a scatter plot of the observed of the daily peak to off-peak spread – the difference between the daily average hourly load during the peak period and the daily average hourly load during the off-peak period – for summer weekdays during 2018 and 2019. The solid and dashed lines display kernel weighted, local polynomial smoothed averages of the peak to off-peak spread conditional on the daily average temperature. The conditional averages were calculated using epanechnikov kernel weights with a $2°F$ bandwidth. The bottom panel displays the observed, and local polynomial smoothed averages, of the daily mid-peak to off-peak spread – the difference between the daily average hourly load during the mid-peak period and the daily average hourly load during the off-peak period – for summer weekdays during 2018 and 2019.