Management Science

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MANAGEMENT SCIENCE
Vol. 69, No. 12, December 2023, pp. 7784–7798
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

https://pubsonline.informs.org/journal/mnsc

Field Experimental Evidence on the Effect of Pricing on Residential Electricity Conservation

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Received: July 17, 2020
Revised: December 10, 2021; April 21, 2023
Accepted: August 23, 2023
Published Online in Articles in Advance: November 7, 2023

https://doi.org/10.1287/mnsc.2020.02074

Abstract. This study examines how electric utilities and regulators can encourage residential consumers to conserve electricity during the hottest summer days and shift electricity load from the day to off-peak, nighttime hours. We analyze a two-year field experiment involving 280 Texas households that explores approaches to conservation and load-shifting to enable emission reductions and reduce generation costs. Our critical peak pricing intervention reduces electricity consumption by 14% on the peak hours of the hottest days, leading to greenhouse gas emission reductions of about 16%. A key contribution of this study is the use of high-frequency appliance-level data. We show that 74% of the critical peak response is from reducing air conditioning. In a complementary nighttime pilot program, consumers respond strongly to lower prices by programming the timing of electric vehicle charging. Our work highlights how automation can influence the consumer tradeoffs relating to effort costs, discomfort, monetary incentives, and warm glow.

History: This paper was accepted by Rajesh Chandy, Special Section of *Management Science* on Business and Climate Change.

Supplemental Material: The data and online appendices are available at https://doi.org/10.1287/mnsc.2020.02074.

Keywords: carbon dioxide emissions • electricity conservation • critical peak pricing • electric vehicles • load-shifting

1. Introduction

Climate change is a crucial issue of our time, and we face major challenges in transitioning to a deeply decarbonized electricity system. One of the primary hurdles lies in adapting to higher proportions of intermittent renewable energy sources, which pose significant difficulties for balancing real-time electricity supply and demand in the absence of large-scale battery storage, particularly during peak demand periods.

In many locations, peak electricity demand occurs during and just after the hottest afternoons of the year. Utilities must maintain sufficient generation capacity to meet these high-demand periods, but peak period generation is often associated with the highest marginal generation costs and emissions. Critical peak pricing strategies temporarily increase the price of electricity during a small number of periods with the greatest need for more electricity generation, usually due to high demand. In contrast to the peak periods during the day, there are also often very low-priced periods at night, especially in regions with abundant wind power. Strategies to lower nighttime electricity rates can be used as a complement to critical peak pricing by encouraging the shifting of loads that are easy to adjust, such as electric vehicle charging, to off-peak hours when marginal generation costs are low. Shifting electricity demand away from the peak has the long-run potential to lower generation costs and emissions, ease the transition to intermittent renewables, and more effectively use the generation assets available in a region.

Therefore, a critical question for business leaders and policymakers revolves around finding ways to cost-effectively influence electricity demand. This paper empirically examines strategies that electric utilities and regulators can deploy to incentivize residential consumers to (i) conserve electricity during summer peak periods and (ii) shift electricity usage from daytime to off-peak nighttime hours. Addressing these questions paves the way for cost-effective climate change mitigation, reduced air pollutant emissions, and lower electricity generation costs, all while ensuring reliable service and affordability.

We begin by analyzing the results of a two-year field experiment involving 280 households in Austin, Texas with two programs of treatments: one in summer critical peak hours and one in shoulder-season off-peak hours. We first show that (i) there is a significant reduction in residential electricity usage in our critical peak pricing (CPP) treatment, and (ii) this reduction is mainly attributed to a reduction in air conditioning usage (about 74% of the total response). We then provide evidence that the nighttime off-peak pricing treatment successfully shifts electricity use from daytime hours to nighttime hours, and this load shift appears to be from changing the timing of charging of electric vehicles. Our study focuses on a neighborhood in Austin with a higher-than-average electric vehicle ownership rate, allowing us to better understand consumer charging behavior.

We calculate that for each of the 27 CPP events, the average reduction in carbon dioxide (CO2), sulfur dioxide (SO2), and nitrogen oxides (NOx) emissions is 7,027 tons, 7,542 lbs, and 10,720 lbs, respectively, when extrapolated to all of Texas. Thus, the energy conservation from CPP comes with real environmental benefits, which we value at $1,721,000 per event based on recent social cost of carbon estimates. The nighttime treatment shifts electricity to a time of day when demand is low and there is more than enough generation capacity. Furthermore, although the marginal emission intensity of the electric grid at night in Texas may be high today, Texas has been building large quantities of wind generation, which tends to generate the most electricity at night, so in a future decarbonizing electric grid, the nighttime electricity could be very clean.

A key contribution of our work is well-identified evidence of the causal impact of CPP during the day and lower prices of electricity use at night using rich appliance-level data. This is the first study to show that the source of energy conservation from CPP is reduced air conditioning and the source of nighttime load shifting is primarily from changing the timing of electric vehicle charging. These results provide guidance for business leaders and policymakers by suggesting that pricing and automation measures hold promise for fostering prosocial behavior and aiding the shift to renewable energy, and they also set the stage for future research on this topic.

The field experiment also includes treatment arms that test how information provision and conservation appeals influence behavior during the same especially hot days and hours as our CPP treatment. These treatment arms do not generate the robust effects we observe in our CPP and nighttime load-shifting treatments, consistent with some recent studies on information treatments (Andor et al. 2022). However, we cannot rule out that information or conservation appeal treatments could have an effect on electricity use.

We do find substantial behavioral changes in our study. We observe reduced electricity use and emissions during 27 of the hottest days over two summers, a time when demand is so high that the most expensive generation is being used, and a shift in electric vehicle load to times with very low demand for electricity. In the future, leveraging these behavioral responses could enable high levels of intermittent renewable generation by helping to accommodate periods of very low renewable generation where a response in demand would be exceptionally valuable.[1] Fundamentally, our results stem from consumer tradeoffs between effort costs and comfort versus monetary incentives and prosocial conservation motivations (Alizamir et al. 2023). As has been shown in recent literature, such as in Bollinger and Hartmann (2020), automation can reduce the effort cost of responding to signals. Our ability to observe the electricity consumption at the appliance level allows us to look at the underlying process for the behavioral response to CPP, showing that it comes about from an end use that is often programmable (air conditioning), thus indicating that consumers are trading off reduced comfort and a minor effort cost to achieve financial rewards and (potentially) a warm glow from conservation.

Furthermore, our appliance-level data reveal that the nighttime load-shifting response appears to be driven by changing the timing of electric vehicle charging, which is a highly programmable and automated response. In fact, it may require only a one-time effort each season. We view this novel electric vehicle result as more suggestive and illustrative due to the relatively small number of electric vehicles and less-than-perfect balance across treatment groups, and see this as an important area for future work. Although the changes in behavior that we observe could be possible without automation, we believe that they are much more likely to be realized in the presence of automation. Indeed, we see our results as having important relevance for understanding behavior moving forward, for many home appliances and electric vehicles are likely to have automation capabilities in the future. Furthermore, these findings relating to automation point to the potential efficacy of an alternative approach for electricity conservation in peak hours: allow households to enroll in automatic control of air conditioning or electric vehicle charging by the utility (a next step in automation beyond a programmable appliance). Automatic control could potentially garner much of the gains from pricing.[2]

Although others have evaluated pricing experiments in different contexts and with different research questions, our study contributes to the literature by quantifying the significant value of flexible electricity demand toward reducing greenhouse gas emissions based on appliance-level experimental evidence in residential electricity conservation from pricing. Ito et al. (2018) study critical peak period pricing and electricity conservation appeals in the context of a major natural disaster in Japan, a very different context than our own, and cannot explore the mechanisms underlying the response with appliance-level data. Jessoe and Rapson (2014) run a field experiment with 250 households in Connecticut to explore how in-home devices that provide real-time information on electricity pricing and consumption influence the total household response to a small number of critical peak pricing events over a two-month time period.

Similarly, Prest (2020) apply a machine-learning method to estimate heterogeneity in the the conservation of electricity in response to a time-of-use pricing scheme in Ireland. Fowlie et al. (2021) show the effect of default options on electricity consumption in a critical peak pricing field experiment in Sacramento, California. Anderson et al. (2019) study a field experiment with Danish electricity customers to look at rebates intended to lower the cost of electricity to shift electricity consumption to lower-demand periods, similar to our off-peak pricing experiment, although with much shorter low-demand periods and no insights into the appliances that drive the results. Other examples of field experimental work on electricity pricing in Texas, such as Royal and Rustamov (2018) and Zarnikau et al. (2015), provide useful evidence but do not have the breadth or depth of our study.

In line with much of the literature performing field experiments in electricity conservation, a limitation of our study is that it focuses on a particular location and has a modest sample size. Accordingly, we view our research as laying additional groundwork for further field experiments to influence electricity demand in other empirical settings.

2. Research Design

2.1. Design of the Field Experiment

The two programs of our field experiment were conducted in 2013 and 2014 in Austin, Texas, and were focused on the Mueller neighborhood. The nonprofit "Pecan Street Inc." is our partner and data provider (see https://www.pecanstreet.org/about/). Households were told that by enrolling they could save on their electric bills and were provided a $200 sign-up incentive for participating regardless of their behavior. The recruitment e-mails also were clear that there was no possibility of a loss (see Online Appendix A for the email text). The recruitment was highly successful, and 256 households in the Mueller neighborhood (out of about 5,000 dwellings) who agreed to participate were included in the experiment, along with 24 from elsewhere in Austin.

The primary reason for the relatively small sample size is that all 280 households in the study had appliance-level electric meters installed on major appliances and circuit-level meters installed in rooms that did not have major appliances. For the 256 households in the Mueller neighborhood, these were installed upon construction of the homes. For the 24 households elsewhere in Austin, these were installed upon participation in any Pecan Street activity (all prior to this experiment).[3]

The 256 households in the Mueller neighborhood were randomly assigned to one of five groups. (1) Control: 57 homes did not receive any treatment during 2013 and 2014. Like the other groups, they also had appliance-level and circuit-level metering. (2) Passive Information: 44 homes were provided access to an online portal that tracks appliance-level electricity use. (3) Active Information: 47 homes were sent a text message appeal 24 hours prior to every CPP event stating "A Pecan Street Project critical peak event is taking place tomorrow from 4 PM to 7 PM." (4) Active Information + Recommendation: 46 homes received the same text message as in (3) along with one of three recommended actions: "Pre-cool your home," "Reduce your air conditioning usage," or "Do not use your clothes dryer." (5) Pricing: 62 homes faced CPP during the summer months (June–September) of 2013 and 2014. They received a text message 24 hours prior to each event stating "Tomorrow is a Critical Peak Pricing event. Your experimental electric rate will be $0.64 per kilowatt hour from 4 PM to 7 PM. Pecan Street Inc. Pricing." During the months of March, April, May, November, and December, when wholesale prices at night are low, they received a text message 24 hours prior to the start of the nighttime pricing stating, for example "Pricing Trial Reminder: November and December are wind enhancement months." The lower experimental price was 2.65 cents/kWh. The 24 homes elsewhere in Austin received no intervention and serve as another control group.

The summer (June–September) electric rate in 2013 was 11.4 cents/kWh and in 2014 was 12.1 cents/kWh for the local utility, Austin Energy. In the winter (October–May) it was 8.7 cents/kWh in 2013 and 8.9 cents/kWh in 2014. Thus, the pricing treatment led to a substantially higher marginal price during the peak event periods and a substantially lower marginal price during the nighttime off-peak event periods. These rates are set based on a negotiation process between the utility and state regulator. Under the standard Austin Energy pricing, peak periods were not priced differently than any other period, so residents would not experience savings from reduced electricity consumption during peak periods besides through the normal cost savings from using less electricity. Twenty-seven critical peak treatment days occurred during the months of June through September 2013 and 2014. These event days were called a day in advance based on the expected temperature (see Online Appendix A for further details). All treated participants were sent an email on their registration indicating that they could save money during peak times by shifting laundry, dishwashing, and air conditioning use to another time.

The randomization occurred once and was used for both programs of the field experiment: the summer CPP program and the winter lower pricing program. In effect, the households in the pricing treatment had their tariffs moved closer to wholesale prices in both the off-peak and summer months. One challenge in the experimental design is that changing electricity rates requires a major process involving the utility and the state regulator, the Public Utility Commission of Texas. Pecan Street has a relationship with customers just like the utility, but is not the actual utility, which is Austin Energy. Thus, to change the effective retail electricity rate, we followed the same approach as in several recent papers, including Wolak (2006) and Gillian (2018). Specifically, Pecan Street set up a credit account for each household in the pricing treatment, which they could view on the online portal. Households received their usual electric bill from Austin Energy but also received a modified bill from Pecan Street. If the bill using the experimental CPP rate was lower (e.g., from the off-peak night program) than the participant's Austin Energy bill, the difference is deposited in the credit account. If the bill using the experimental rate was higher (e.g., from critical peak pricing), the difference was deducted from the account. The participants in the experiment had their balances adjusted every month with their regular bill, and at the end of both pricing experiments in October 2014, participants were issued a payment.

If there are behavioral biases, the effect of this payment scheme may not exactly match the effects of critical peak pricing performed by the utility that directly changes the single electricity bill. Pecan Street attempted to mitigate this as much as possible by communicating the critical peak prices in the text message and by emphasizing in email communications that the household's true electric bill is the Pecan Street bill. At the end of the experiment, 97% of the pricing participants had positive credits, implying that they saved money from their actions under the experiment. The average payment was \$125.13, and the highest payment was \$260, plus the \$200 flat-rate participation payment that all participants in all treatment groups received (so the largest overall payment was \$460).

Because of the possibility of site selection bias, it is worth considering how representative the Mueller neighborhood is of the city of Austin. In Online Appendix A, we compare Census demographic data from 2014 for the Mueller neighborhood and the city of Austin (see Table A.1). Our comparison of observables indicates that households in the Mueller neighborhood are quite similar to the average household in the city of Austin. In fact, the confidence intervals overlap in five of the eight observables. There are some differences. Households in the Mueller neighborhood are very slightly wealthier and better educated than households in Austin as a whole. Not surprisingly, because the homes are relatively new, the median home value for owner-occupied housing units is higher than average in the city of Austin. However, the number of rooms in the homes is slightly smaller. The sample also contains more households with electric vehicles (56 households; 22% of the sample) than the average electric vehicle market share of new cars in Texas in 2013–2014, which is under 1% (it is nearly 4% in 2023Q1). This provides an important opportunity to explore load shifting of electric vehicle charging, but also points to a limitation of the study in that our population is representative of early adopters of new technologies rather than the mainstream population.

Indeed, we are cautious in extrapolating our results too far beyond Austin, especially for our nighttime program. They are likely the most applicable to other settings in the south and southwestern parts of the United States that have similar climates, demographics, and affinity for new technology (e.g., certain neighborhoods in Albuquerque, San Antonio, Dallas). The additional 24 households outside the Mueller neighborhood provide some further evidence on external validity to the rest of Austin.

3. Data, Econometric Analysis, and Results

3.1. Data

The primary outcome variable in our study is electricity consumption. We have unique minute- and appliance-level electricity consumption data for each household from March 2013 through October 2014. Appliances that are separately metered include HVAC and other air conditioning units, refrigerators, electric vehicle chargers, clothes washers and dryers, dishwashers, ovens, and electric water heaters. In addition to the separate appliances, circuit-level meters are also included when there are circuits for specific rooms. For example, there are readings for bedrooms, kitchens, and bathrooms. Our data also contain a variable for total electricity consumption, which may include some electricity usage that is not individually metered. There are roughly 200 million observations in our data set. Before performing any analyses, we conduct some minor data cleaning (see Online Appendix B.1 for details).

Table 1 presents a summary of electricity usage data by period: summer (June–September), nonsummer (all other months), and the summer critical peak pricing periods. We have minute-level data in units of kWh per minute. In Panel A, we divide observed appliance-level electricity consumption into two broad categories: adjustable consumption and unadjustable consumption. Adjustable consumption refers to sources that are likely to be easily switched up and down, for example, air conditioning, and clothes washing and drying. Many of these end uses are programmable. In non-summer periods, adjustable

Table 1. Use by Major Category (Percent)

Variable	Non-summer	Summer	Event period
Panel A: Use by major category			
Adjustable	39.3	58	72.8
Unadjustable	8.3	5.2	4.3
Unmeasured	52.4	36.8	22.9
Panel B: Use by major appliance			
Heating/cooling	15.7	44.9	63.2
Washer/dryer	2.9	1.6	1.0
Kitchen	9.1	5.2	4.4
Electric vehicle	4.6	2.9	2

Notes. The values in Panel A add up to 100%. "Unadjustable" refers to appliances such as refrigerators that must run all the time. "Adjustable" refers to usage from individually metered appliances that can easily be turned up and down (e.g., air conditioners, clothes washers, dryers, etc.). "Unmeasured" is the difference between total consumption and the sum of the adjustable and unadjustable individually metered usage, and it includes any appliance that does not have an individual meter. Panel B includes selected metered appliances and thus does not add up to 100%.

consumption is just under 40% of the total on average, but it increases to 58% of consumption in the summer and 73% of consumption during event periods. Unadjustable consumption refers to sources that run all the time, such as refrigerators. In non-summer months, this makes up 8% of consumption, but it drops to 5% in the summer months and to 4% during event periods. As mentioned previously, not all electricity usage is individually metered. Thus, we have a third category for unmeasured electricity consumption, which is equal to the total electricity consumption minus the sum of the measured consumption. In non-summer months, this is more than 50% of consumption, as might be expected due to the many small appliances in a typical household (e.g., computers, phone chargers, hair dryers, electric tools). In summer periods, this drops to 37%, and in event periods, it drops further to 23%. The three categories sum up to 100%.

In Panel B of Table 1, we include four of the most important individually metered uses. In the winter, heating is primarily natural gas heating, with electricity used to run the fan. In the summer, cooling is via air conditioning. The data contain consumption by central air conditioning as well as window units, and we aggregate these together into a single "AC" variable. We see that in the non-summer months, heating and cooling constitute 16% of electricity use. In the summer months they constitute 45% of electricity use and during event days they reach 63% of electricity use, dominating electricity use. In contrast, washers and dryers constitute 3% of electricity use in the non-summer months and less than 2% during the summer or event days. These summary statistics provide a glimpse into the unusually rich nature of our data and illustrate how heating and cooling are the most important electricity service demands. For the households in the pricing and other treatment groups that have electric vehicles, electric vehicle electricity use makes up 5.7% of total use (averaged over minutes).

Next, we examine the balance of observables between the control group and the treatment groups to assure that our randomization was carried out effectively. For this, we relied on a survey of all households performed at the beginning of the field experiment. Of the 280 households in the study, we received survey responses from 162 households. Table 2 displays the balance of observables between households in the control group and households in the treated groups (see Online Appendix B.2 for the breakdown by each treatment). With the exception of the presence of an electric vehicle, none of the observables are statistically different between the control

Table 2. Balance of Observables

	Control		Treatment			
	Mean	Standard deviation	Mean	Standard deviation	Mean difference	p value
Nonevent day 4 to 7 PM electric use (kWh/min)	2.58	2.32	2.82	2.49	−0.24	0.14
Pretreatment electric use (kWh/min)	0.82	1.19	0.98	1.6	−0.15	0.054
Income (categorical)	4.61	1.27	4.25	1.39	0.36	0.17
Education (categorical)	1.58	0.57	1.63	0.59	−0.05	0.67
Preferred thermostat temperature (°F)	76.74	2.23	76.93	2.47	−0.19	0.67
Number of televisions	1.72	1.06	1.74	0.92	−0.02	0.92
1 (has solar PV system)	0.08	0.27	0.18	0.38	−0.10	0.12
1 (has electric vehicle)[a]	0.14	0.12	0.51	0.24	−0.37	0.00
1 (has programmable thermostat)	0.68	0.48	0.76	0.43	−0.08	0.44
Number of residents	2.34	1.07	2.44	1.32	−0.10	0.67
Square footage of house	1,889	612	2,076	705	−187	0.25

Notes. Data on demographics was obtained from the Pecan St. survey. An observation is a household. Average income is approximately $85,000 for treatment and control groups. Some houses only responded to certain questions, hence the number of observations varies by observable. The number of observations for each observable are as follows: N income = 107, N educ = 110, N temp = 109, N number of televisions = 110, N solar pv = 110, N residents = 99, N house square footage = 88, N programmable thermostat = 87.

[a]EV is only for the pricing and control groups as we only evaluate electric vehicle use during the off-peak pricing trial. Adding all information treatment groups to the control group increases the proportion of houses in the control group with EVs to 34% (25 houses with EVs in the expanded control group). This expanded sample is used in Table 4 and described in the text. The pretreatment period is defined as March–May 2013.

and treatment groups at even a 5% significance level. We did not randomize based on the differences in electric vehicles across treatment groups, and the differences across treatment groups are an unfortunate result of randomization with a relatively small sample. We very carefully analyze the electricity use in the pretreatment period and perform robustness checks but view our results relating to electric vehicles as more illustrative than our causal results relating to the use of other appliances, which are quite balanced across treatment groups. Row 1 of Table 2 indicates there is no statistical difference between treatment and control group nonevent day electricity use, which is a useful placebo test indicating that the randomization was effective with respect to electricity consumption.[4]

3.2. Summer Event Treatment Effects

Our empirical specification for the average treatment effect (ATE) for all summer treatments j is the following linear equation:

$$Y_{it} = \sum_j \beta^j T_{ijt} + \mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\rho_i} + \boldsymbol{\phi_t} + \varepsilon_{it}, \qquad (1)$$

where Y_{it} is the electricity use by household i in minute of the sample t. T_{ijt} is a dummy variable indicating that household i is in treatment group j and receives the treatment in time t (i.e., it is an event hour on an event day and the household is treated); $\boldsymbol{\rho_i}$ are household fixed effects to control for unobserved heterogeneity at the household level; $\boldsymbol{\phi_t}$ is a set of quarter-hour of the sample fixed effect (i.e., fixed effects for each 15-minute interval of the sample) to control for time-specific demand shocks; and $\mathbf{X}$ is a vector containing any remaining interactions not subsumed by the fixed effects (e.g., it is an event day and the household is treated with one of the treatments, or it is a peak time and the household is treated).[5]

Our econometric specification in (1) can be viewed as a triple-differences specification in that it exploits variation across treatment and control, across critical peak days and nonpeak days and across treatment and nontreatment hours.[6] Identification fundamentally relies on the randomization of the field experiment but further benefits from comparing differences in trends in the triple-difference. We cluster standard errors at the household level to account for any pattern of household-level correlation across the residuals (our results are robust to also clustering at the daily level).[7]

3.2.1. Primary Results. Column (1) in Table 3 presents our raw results without any household or time fixed effects. We observe that for all but the pricing treatment, there is very little difference in electricity consumption between the treatment groups and control group. Looking at the mean during the treatment period, the pricing treatment effect (−0.39 kWh per minute) amounts to about a 14% reduction in use.

Column (2) in Table 3 presents our main results from estimating Equation (1), which controls for household and time fixed effects. Relative to the control group, the results show no statistically significant effects for the online portal, text message, and text message + recommendation treatment. It is important to note that, although the information treatment point estimates are close to zero and not statistically different from zero, the lower bound of the text + action treatment 95% confidence interval (CI = −0.197, 0.117) is nearly the same as the upper bound of the pricing treatment

Table 3. Summer Event Treatment Effects

β^j coefficients	(1) Electricity use	(2) Electricity use	(3) Adjustable(include AC)	(4) Nonadjustable	(5) AC only
Pricing	−0.39***	−0.39***	−0.38***	−0.001	−0.29***
	(0.09)	(0.09)	(0.10)	(0.002)	(0.08)
Text + action	−0.04	−0.04	−0.10	−0.001	−0.08
	(0.07)	(0.08)	(0.08)	(0.001)	(0.07)
Text message	0.05	0.04	−0.003	0.005	−0.02
	(0.08)	(0.08)	(0.10)	(0.003)	(0.08)
Portal	0.02	0.02	−0.07	−0.001	0.01
	(0.08)	(0.08)	(0.08)	(0.001)	(0.06)
Household fixed effects	No	Yes	Yes	Yes	Yes
Quarter of sample fixed effects	No	Yes	Yes	Yes	Yes
R^2	0.03	0.16	0.09	0.24	0.06
N	194m	194m	145m	194m	145m

Notes. Column (1) does not include any fixed effects, but includes all triple difference variables. Dependent variable in columns (1) and (2) is total electricity use, in (3) is electricity use from all adjustable appliances (e.g., air conditioners, washers, dryers, etc.), in (4) is electricity use by nonadjustable uses (e.g., refrigerators), and in (5) is electricity use by air conditioners (AC) only. Triple-difference coefficients shown; all other interactions in (1) are included. An observation is a household-minute and electricity use is in units of kWh per minute. Standard errors clustered on i in parentheses. The number of observations changes in each column because not all households have everything individually-metered. The average control group usage during the event periods is 2.79 kWh per minute.

***$p < 0.01$.

Management Science, 2023, vol. 69, no. 12, pp. 7784–7798, © 2023 The Author(s)

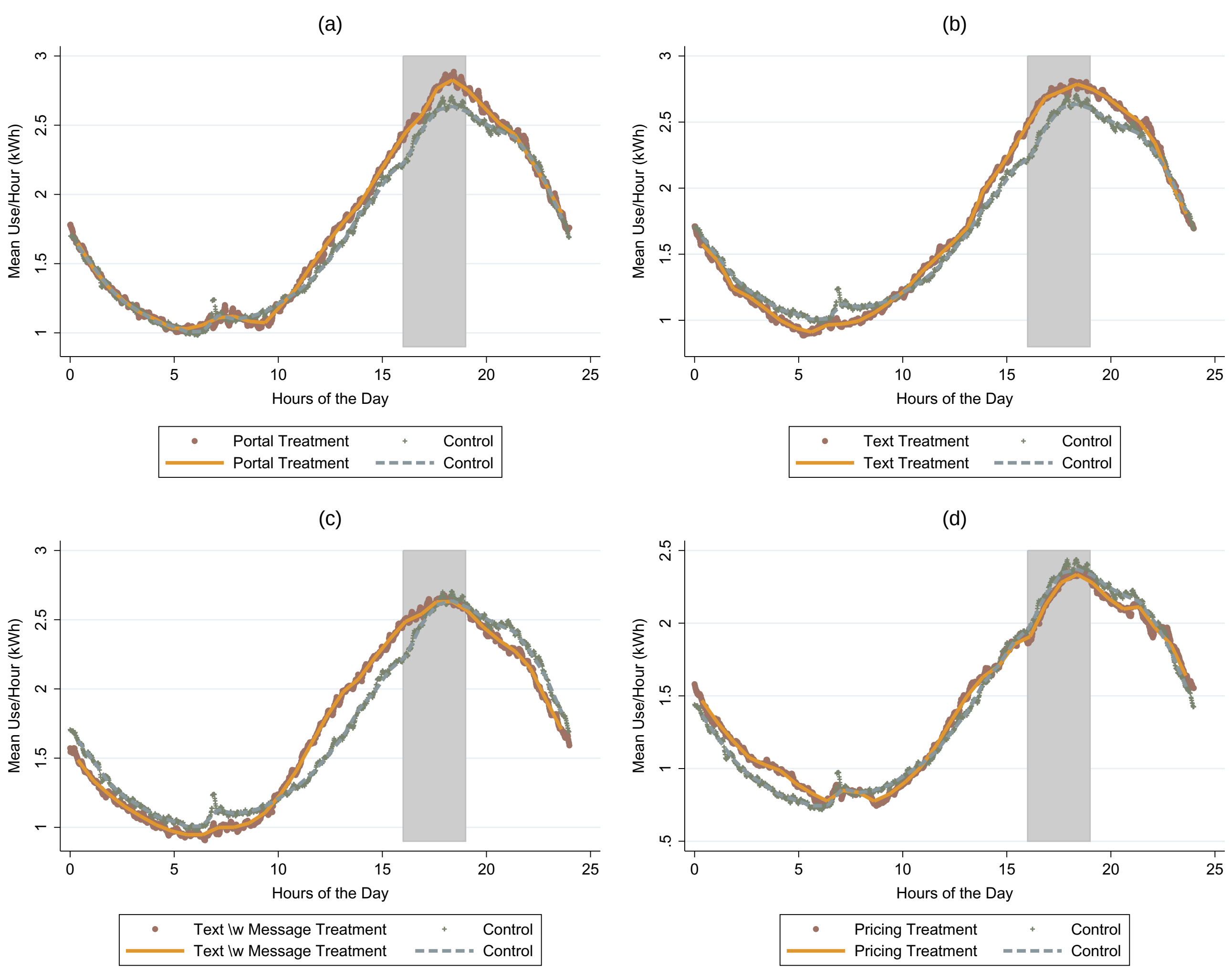
95% confidence interval (CI = −0.586, −0.194). Our experiment may be underpowered to detect small effects from information if they are present.[8]

One might conjecture that there would be a large and significant effect from information provision based on findings in the previous literature (Tucker and Zhang 2010, 2011; Bollinger et al. 2011; Grubb and Osborne 2015). However, this might be countered by the effort and discomfort costs from reducing AC use on hot summer days that may make information alone less effective. Indeed, recent evidence suggests that information alone is not always effective (Andor et al. 2022). Furthermore, there may be information overload from the large amount of information on the online portal (Bettman et al. 1998, Chen et al. 2009). Although our results are not by any means definitive on the effect of information, we found the contrast between the information treatment coefficients and the significant and much larger coefficient on the pricing treatment to be notable.

Our coefficient estimates in Table 3 indicate that pricing reduces event period electricity use by 0.39 kWh per minute. The average electricity consumption during the event hours for the control group is 2.79 kWh per minute, so this can be seen as a 14% decrease in electricity consumption, which exactly matches the decline the raw data.[9] For comparison, this decrease in electricity consumption is equivalent to a savings of \$0.75 per event per household or \$20.22 per event per household across the 27 event periods.

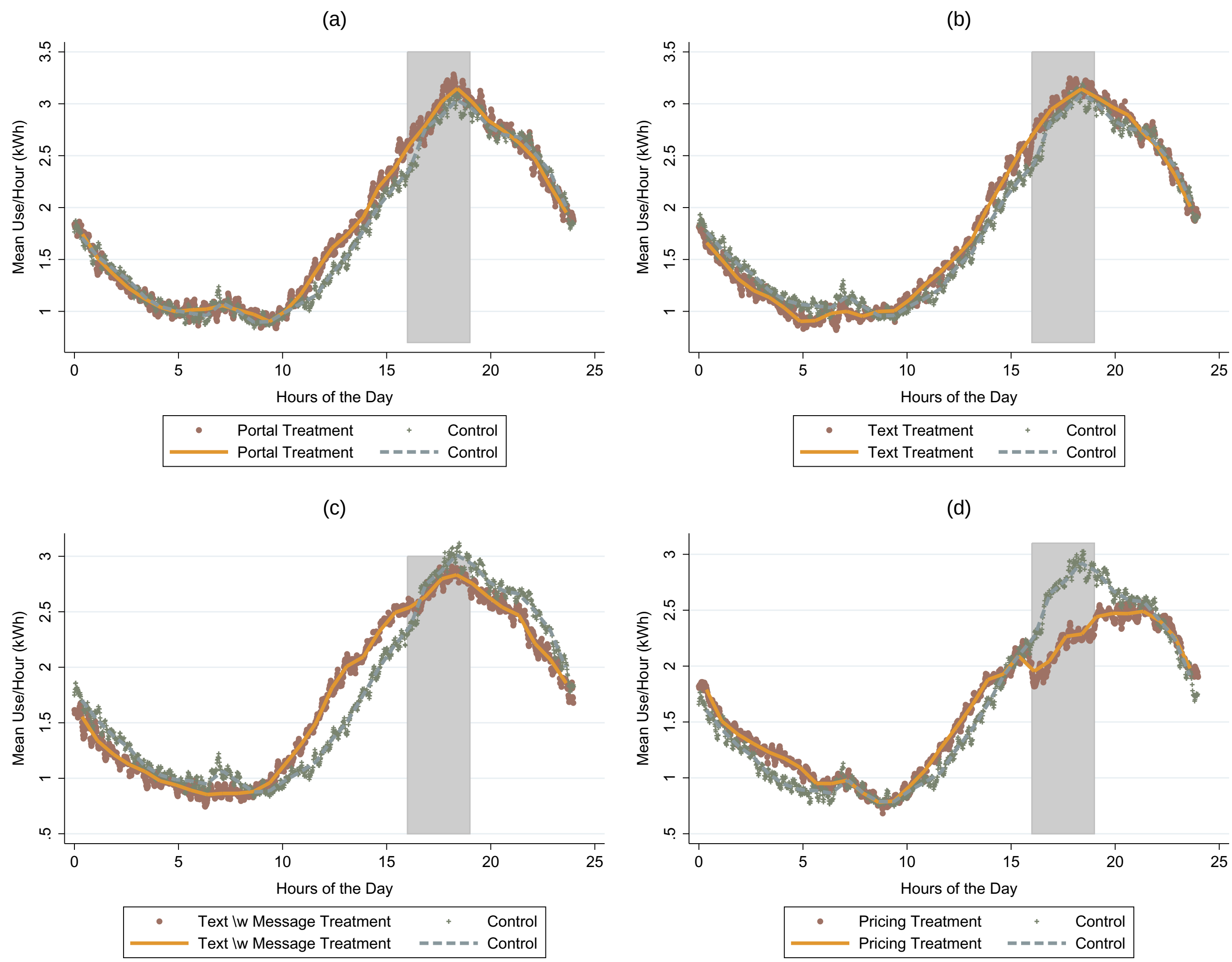
To visually demonstrate these core results of the paper, we present a series of figures. We begin with nonevent days when no treatment occurs to show just how similar the patterns of electricity consumption are between the pricing treatment group and control group. Figure 1 presents electricity usage by minute on average for all nonevent days in our sample for the pricing treatment group.[10] For reference, the event day treatment period is shown by the shaded areas,

Figure 1. (Color online) Nonevent Day Mean Minute Level Use by Treatment Group Net of a Household Fixed Effect



Notes. Shaded region is treatment period. (a) Portal treatment. (b) Simple text message treatment. (c) Text with message treatment. (d) Pricing treatment.

Figure 2. (Color online) Event Day Mean Minute Level Use by Treatment Group Net of a Household Fixed Effect



Notes. Shaded region is treatment period. (a) Portal treatment. (b) Simple text message treatment. (c) Text with message treatment. (d) Pricing treatment.

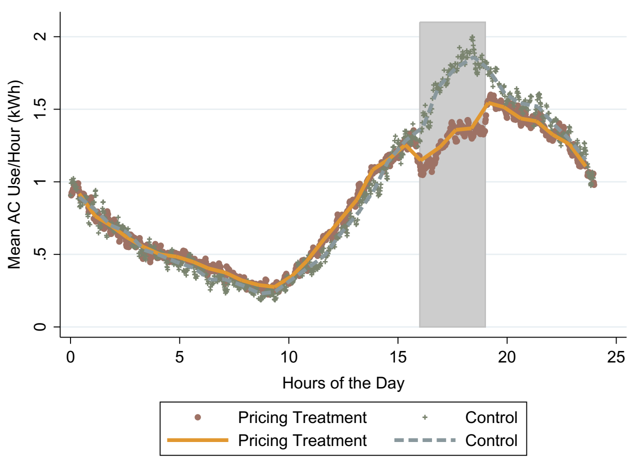
although no treatment is occurring. We observe no difference between the pricing treatment and control.[11]

Figure 2 presents the same figure for the pricing group in critical peak event days only. We see that the treatment and control groups are nearly identical for most hours, but there is a large reduction in electricity usage during the treatment hours. This is an important observation as it shows that there is no evidence of load shifting (i.e., total daily consumption declines), which could limit emission reductions. Table C1 in Online Appendix C.5 shows that when we econometrically estimate hourly treatment effects, we again see no evidence of load shifting.

3.2.2. Appliance-Level Results. We now turn to results leveraging our appliance-level data. Columns (3) and (4) of Table 3 replace Y_{it} in (1) with electricity use from major categories, as previously defined in Table 1. Column (3) shows that the reduction in electricity consumption from adjustable uses across treatments is very similar to the total reduction in column (1).[12] The treatment effect for pricing is almost identical in columns (2) and (3), suggesting that the reduction in electricity usage can be attributed entirely to adjustable uses. Column (4) presents results for nonadjustable uses, and it shows no statistically significant effects for any of the treatments, as would be expected.[13]

A reasonable conjecture is that adjustable uses are the ones where a consumer is balancing effort costs and disutility from reduced comfort against monetary rewards, and thus these would be the uses where we see an adjustment. We can dive deeper into this conjecture in column (5) of Table 3, which focuses on air conditioning. As we showed in Table 1, air conditioning comprises 63% of electricity use during event days and is an adjustable and programmable electricity use that inherently involves consumers making tradeoffs between effort costs, comfort, and monetary costs, so one might expect much of the response to be from this use. The results show a reduction of 0.29 kWh per minute from air

Figure 3. (Color online) Event Day Mean Minute Level Air Conditioning (AC) Use for the Pricing Treatment and Control Groups Net of a Household Fixed Effect



Note. Shaded region is treatment period.

conditioning use alone for the pricing treatment group: 74% of the total reductions in electricity use. Figure 3 visually presents the treatment effect on air conditioning use on event days, showing a pattern that is almost identical to the pattern in Figure 2. Online Appendix E presents the results for other major electricity uses, for which we see minimal effects from the pricing treatment, underscoring the importance of air conditioning.

3.2.3. Heterogeneity Analysis. We also explore heterogeneity in the treatment effects. The most interesting finding comes from interacting the pricing treatment dummy with the billing tier that the customer is on. All the customers in our sample are on an increasing tier schedule for their electricity rates, whereby households face a higher marginal price if they consume more electricity. Table D1 in the online appendix shows that households on the lowest tiers (i.e., consume the least) show a much larger response (in terms of kWh conserved) than households on the highest tier. This result may be because those on the lowest tier are much more cognizant of their electricity use and perhaps face lower discomfort costs and effort costs. We also explore interactions with demographics, but find mostly insignificant results.

3.2.4. Robustness Checks. We perform a series of robustness checks (see Online Appendix C.1). We exploit different sources of variation and find that our results are quite robust. We also estimate our primary specification with a logged dependent variable and aggregate to 15-minute-level data instead of minute-level data and find nearly identical results.

We next replace the control group in our estimations with a control group of 24 households elsewhere in Austin and find similar results (Table C1 in the online appendix). This last robustness check with the Austin-wide control group suggests that our results likely have at least some external validity beyond the Mueller neighborhood. Finally, we limit the sample to households with similar demographic characteristics to Texas more broadly. We estimate our primary specification on this subsample to explore external validity relative to the rest of Texas (based on observables). Despite a reduction in sample size, the results are robust (see Online Appendix C.2). For more robustness tests that provide some evidence on mechanisms, see Online Appendices C.3 and C.4, where we find evidence indicating that households did not precool their homes (perhaps due to the effort costs) and that people did not leave their homes during the critical peak hours.

3.3. Nighttime Off-Peak Pricing Treatment Effects

In the nighttime off-peak pricing program, households who were randomized into the pricing treatment group receive a text message at the beginning of each off-peak month (March, April, May, November, December) letting them know that their effective price from the hours 10 PM to 6 AM is \$0.0265 per kWh for that month.[14] Harding and Lamarche (2016) find load shifting from households with programmable thermostats, and thus a reasonable conjecture is that we will see some changes in electricity use, especially from thermostat settings and electric vehicle charging, which requires minimal effort to program to complete charging by a certain hour. Accordingly, we focus our analysis on total electricity use, electric vehicle charging, and heating. As mentioned previously, a limitation of this analysis is that electric vehicle ownership is not perfectly balanced across treatment groups. Thus, it is especially important to look at electricity consumption outside of the treatment period to assure it is similar across the control and pricing groups. One could also view these results as a "proof of concept" intended to lay the groundwork for further research in this area.

We begin by examining the average treatment effect during nighttime hours. Here we only include households in the pricing treatment and control group and over the relevant (off-peak) months. We also exclude the daytime hours to account for load shifting. We estimate the following linear specification:

$$Y_{it} = \sum_{h} \beta^h T_{iht} + \boldsymbol{\rho_i} + \boldsymbol{\phi_t} + u_{it}, \tag{2}$$

where Y_{it} is again electricity use by household i in minute t, T_{iht} is a dummy for being a treated household during the hour of the night h, where h is each hour over the night from 10 PM to 6 AM (or an average over several of the hours). As before, $\boldsymbol{\rho_i}$ are household fixed effects, and $\boldsymbol{\phi_t}$ are fixed effects for each 15-minute interval in the sample.

Table 4. Nighttime Off-Peak Pricing Experimental Program

	Original sample			Expanded control	Matched sample
	(1) Use	(2) EV	(3) Heating	(4) EV	(5) EV
1 (treated × 10 PM to 2 AM)	0.02	−0.08	0.01	−0.07	−0.01
	(0.07)	(0.07)	(0.05)	(0.06)	(0.09)
1 (treated × 2 AM to 6 AM)	0.13*	0.11*	0.01	0.11**	0.17**
	(0.07)	(0.06)	(0.06)	(0.05)	(0.09)
Household fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter of sample fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.15	0.09	0.11	0.07	0.02
N	30m	13m	30m	20m	12m

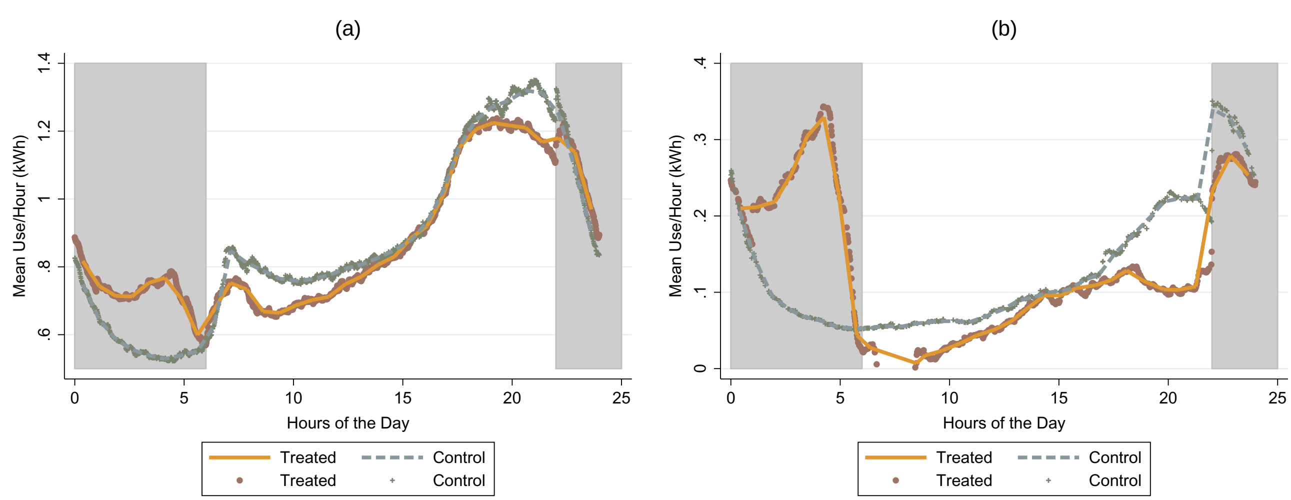
Notes. Dependent variable in (1) is total electricity use, in (2), (4), and (5) is electric vehicle use, and in (3) is heating electricity use. Only triple-difference coefficients shown; all other interactions in Equation (2) are included. An observation is a household-minute and electricity use is in units of kWh per minute. Regressions only include off-peak period hours (10 PM to 6 AM) to exclude load shifting effects during nontreatment hours as evidenced by Figure 4. Columns 1–3 use the original sample of houses. Column 4 adds control houses from the information treatment groups. Column 5 matches treated houses to control houses in the original control group based on pretreatment EV usage. The average control group usage during the nighttime period is 0.66 kWh per minute. Standard errors clustered on i in parentheses.

$^*p < 0.1$.

For ease of presentation, in Table 4 we present coefficients for two four-hour time frames of night hours: 10 PM to 2 AM and 2 AM to 6 AM.[15] Column (1) presents the results for all electricity uses, column (2) for electric vehicles, and column (3) for heating. We find an average increase in total electricity consumption in the 2 AM to 6 AM off-peak hour window of 0.13 kWh per minute (p = 0.063 and 95% CI = −0.007, 0.267). This is a large increase, and it is even more dramatic if we examine the treatment effect by hour (by interacting with each hour separately rather than the two four-hour time frames). For example, between 3 AM and 4 AM, we see an increase of 0.18 kWh per minute ($p < 0.05$ and CI = 0.023, 0.337). There is also a significant effect for the hours 2 AM to 3 AM that is similar in magnitude to the effect for 3 AM to 4 AM. Figure 4 visually illustrates these findings by hour. Looking over the entire day, we see that the response to the night pricing is almost entirely load-shifting, so that total electricity consumption over the day does not change.

The coefficient in column (2) indicates that 85% of the overall increase in electricity consumption during the night off-peak hours is from the charging of electric vehicles, highlighting that electric vehicles have potential to help manage electricity load due to the minimal effort cost to program the charging.[16] Notably, when put in terms of elasticities, the response to the night price decrease (price elasticity = −0.28 (95% CI = −0.58, 0.02)) appears to be greater than the response to the CPP increase (price elasticity = −0.03

Figure 4. (Color online) Event Period Mean Minute Level Total Use and Electric Vehicle Use for the Night Low Pricing Treatment and Control Group Net of a Household Fixed Effect



Notes. Shaded region is treatment period. (a) Total use. (b) Electric vehicle use.

(95% CI = −0.06, −0.02)). This result is likely due to the ease of automation (a single one-time action can adjust charging times for the entire season) and the fact that there are minimal or no discomfort costs from the action. As electric vehicles become more common, this finding suggests that nighttime low pricing will be increasingly valuable by encouraging households to shift the charging of electric vehicles to low-cost or low-emission hours. The potential may be even greater when electric vehicles can send power back to the electric grid, otherwise known as "vehicle-to-grid." The results in column (3) show that heating plays a much smaller role in the response to the lower prices at night, likely because the effort and discomfort costs weigh heavily against the modest financial incentive (in contrast to the large incentive from the CPP).

As mentioned previously, we do not have perfect balance between the pricing treatment and control group in electric vehicle ownership, which may raise sample selection concerns. Figure 4 very clearly shows that the treatment and control groups had extremely similar electricity consumption outside of the treatment period, which is very helpful for internal validity. In columns (4) and (5) of Table 4, we present further evidence supportive of the internal validity of the analysis. First, we use a larger control group that also includes the control homes from elsewhere in Austin (column (4)). This brings the fraction of electric vehicles in the control group to 34% (versus 37% in the treatment). The results are comparable to our primary results. Second, we use a matching estimator, where we match on pretreatment electric vehicle use (see Online Appendix C.5 for details). The results are again similar (column (5)). Although these robustness checks do not eliminate the limitation of our "proof-of-concept" analysis, they suggest that sample selection is less likely to be biasing our results.

4. Implications for GHG Emissions and Cost Savings

In the current Texas electricity system, the time of the day with the lowest prices (and lowest marginal generation cost) is almost always at night, due to low demand for electricity and high generation by wind in West Texas. In the future, with continued building of wind generation, it is likely that the marginal emissions at night could be very low. However, at the moment, coal-fired generation is sometimes used as the marginal generator at night in Texas. Thus, the lowest-cost time of day (at night) may be the time with the lowest *average* emissions but not necessarily the time of the lowest *marginal* emissions, leading to a tradeoff today between lowering the overall cost of electricity generation and lower emissions. This tradeoff will disappear over time with higher levels of renewables and retirements of coal plants. Indeed, the ability to use pricing and automation to shift electricity use could also be used in the future to optimally increase use at the times of the lowest greenhouse gas (GHG) intensity depending on the development of different renewables.

To estimate the impacts on emissions and costs, we bring together data on marginal emissions and the marginal costs of generation at the hourly level. We begin by estimating the marginal emissions by hour of day for carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen dioxides (NO_x) following Holland et al. (2016). We perform this analysis for summer peak periods (4 PM to 7 PM) and off-peak night hours (10 PM to 6 AM). Online Appendix F provides estimation details.

4.1. Emissions Reductions

Applying the marginal emission factors to our field experiment results allows us to calculate daily emission reductions (Table 5). For these illustrative calculations, we scale the results to all residential households in Texas, assuming a similar effect if all received the CPP treatment and responded similarly to those in our field experiment.[17] Panel A shows an average reduction in CO_2, SO_2, and NO_x emissions of 7,027 tons (16% reduction), 7,542 lbs, and 10,720 lbs, respectively. Using a \$185/ton social cost of carbon (Rennert et al. 2022), a \$92,000 per ton cost of SO_2, and a \$14,000 per ton cost of NO_x (EPA 2013), these figures translate to a reduction of \$1,299,999, \$346,923, and \$75,044 per CPP event period, respectively. The reduction in the social costs from CO_2 emissions is equivalent to driving a Ford F-150 approximately 15 million fewer miles.[18] Panel A also displays the impacts of the CPP on air conditioning alone, which amounts to roughly 75% of the total benefits.

One natural question that arises when thinking about these results is how much additional energy, and therefore emissions, will be required to keep homes cooled to preferred temperatures as outdoor temperatures increase from human-induced climate change. Panel B of Table 5 provides the emission reduction estimates for a 1°F and 3°F change in air conditioning thermostat setting (see Online Appendix F for calculation details). These results show the potential added costs and emissions (if we had today's electric grid) from increases in temperature due to climate change.

Panel C of Table 5 displays the additional emissions and social costs of these emissions associated with the increase in electricity use from the nighttime off-peak treatment, extrapolated to all registered vehicles in Texas for illustrative purposes.[19] We find that the increase in emissions is relatively small, and not too different than if the electric vehicles are charged during the day. This finding would change over time if much more

Table 5. Emissions

	CO_2	SO_2	NO_x
Panel A: Critical peak pricing emissions			
Total use emissions reductions (tons (lbs)/Texas/event)	−7,027.02	−7,541.82	−10,720.71
Social cost of total use emissions reductions ($/Texas/event)	−1,299,999	−346,923	−10,720
AC emissions reductions (tons (lbs)/Texas/event)	−5,225.22	−5,608.02	−7,971.81
Social cost of AC emissions reductions ($/Texas/event)	−966,666	−257,969	−55,803
Panel B: Additional cooling emissions			
Emissions from 1°F (tons (lbs)/Texas/evening)	522.52	560.8	797.18
Social cost from 1°F ($/Texas/evening)	96,667	25,797	5,580
Emissions from 3°F (tons (lbs)/Texas/evening)	1,567.57	1,682.4	2,391.54
Social cost of 3°F ($/Texas/evening)	290,000	77,391	16,741
Panel C: Wind pricing emissions			
Emissions from additional nighttime use (tons (lbs)/all EVs/nighttime)	16.41	25.48	16.36
Emissions if charged during day (tons (lbs)/all EVs/daytime)	16.06	23.93	16.28
Additional emissions from change in charging profile (tons (lbs)/all EVs/treatment period)	52.92	232.03	12.21
Social cost of additional emissions ($/all EVs/treatment period)	44,433	10,674	85

Notes. Panel A displays emissions reductions from the CPP treatment effect for a single event period. Tons are used for CO_2, whereas pounds are used for SO_2 and NO_x. Results are extrapolated to 11,000,000 houses in Texas. The CPP emissions reductions are approximately 16% of total emissions during an average event period. Panel B displays the additional emissions and social cost of emissions from a 1 or 3°F increase in temperatures above the preferred thermostat setting. Texas is expected to experience a 3°F increase in average temperatures by 2050. The numbers are for 11,000,000 houses in Texas for a single three-hour peak period. Panel C displays the emissions from the additional EV charging at night relative to charging in the daytime. We use a social cost of carbon of $185 per ton. We use a $92,000 per ton cost of SO_2, and a $14,000 per ton cost of NO_x.

wind generation is built in the Texas electric grid. The social costs of the additional emissions, even with the electric grid today, are modest ($55,192 total across the three pollutants).

4.2. Generation Cost Reductions

In addition to emissions, generation costs are also important, as they determine the affordability of electricity and thus the likelihood that households will electrify end-uses that are currently most often powered by fossil fuels (e.g., vehicles, heating). We bring in data on hourly load and generation from the independent system operator on the Texas electric grid, ERCOT, for 2013 to 2020.[20] We also bring in an estimate of the hourly marginal costs ("system lambda") from Federal Energy Regulation Commission Form 714. We multiply the marginal costs during the CPP periods by the CPP electricity reductions.

In Panel A of Table 6, we find a reduction in generation costs of $0.059 per house per treatment period or $652,419 if all houses in Texas received the treatment, a value far greater than the cost of the treatments. Panel B displays the additional generation costs associated with warmer outdoor temperatures, which shows that a one degree increase in temperature would add $48,513 in generation costs per evening in Texas. One limitation in

Table 6. Generation Costs

Panel A: Critical peak pricing costs	
CPP generation cost reductions ($/house/event)	−0.059
CPP generation cost reductions ($/Texas/event)	−652,419
Panel B: Additional cooling costs	
Generation costs from 1°F ($/Texas/evening)	48,513
Generation costs from 3°F ($/Texas/evening)	145,540
Panel C: Wind pricing costs	
Generation cost during night ($/house/nighttime)	0.012
Generation cost during night ($/all EVs/treatment period)	98,066
Generation cost during day ($/house/daytime)	0.016
Generation cost during day ($/all EVs/treatment period)	124,223
Reduced generation costs from change in charging profile ($/all EVs/treatment period)	−26,157

Notes. Panel A displays generation cost reductions from the CPP treatment effect for a single event period. Results are extrapolated to 11,000,000 houses in Texas. Panel B displays the additional generation cost from a 1 or 3°F increase in temperatures above the preferred thermostat setting. The numbers are for 11,000,000 houses in Texas for a single three-hour peak period. Panel C displays the generation costs from charging EVs during the nighttime treatment period, from charging EVs during the daytime control period, and the difference in generation costs between the two.

this calculation is that the generation mix and marginal cost of generation are likely to evolve over time, but this calculation provides a useful benchmark given today's electric grid.

In Panel C of Table 6, we present illustrative calculations showing that our field experiment results, when extrapolated to electric vehicles in all of Texas, suggest savings of $26,157 over the treatment period by shifting electricity use from the day to the low-cost night hours. This is approximately 50% of the additional social costs of the emissions from the switch, so the switch to EV charging during night hours is net negative from a social perspective given the current generation portfolio. Yet, this simple analysis misses the long-run potential of load shifting to different times through automation, which could allow for the electric grid to accommodate greater amounts of intermittent renewables while keeping the lights on.

5. Conclusions

This paper examines interventions for electricity conservation and load shifting to reduce generation costs and emissions. A unique aspect of the study is the use of appliance-level data to provide the first evidence on the large contribution of air conditioning to the critical peak pricing response and electric vehicle charging during off-peak times. Greater use of the demand side interventions in our study holds potential to allow utilities to better balance electricity supply and demand, and consequently enable a greater market share of intermittent renewables on the electric grid.

A theme that runs through these results is the tradeoff that households are making between comfort and effort costs to change behavior vs. financial rewards and prosocial warm glow motivations. Another key theme is that automation allows for greater responses, as air conditioning temperature settings and electric vehicle charging can be readily programmed. In the future, automation may have great potential to allow homeowners to program a variety of appliances to allow them to respond to price signals from the utility (Bollinger and Hartmann 2020).

These findings have important implications for the environment and climate by showing that CPP can result in notable emission reductions of carbon dioxide and other air pollutants. The nighttime program served as a "proof-of-concept" for how consumers could be incentivized to change the timing of load. Such a behavioral response is likely to be very important in a deeply decarbonized electricity system with high levels of intermittent renewables, as there will be periods of very low-cost clean electricity flooding the system, which would be optimal periods to charge electric vehicles.

Our study does have limitations. It is a randomized controlled trial with self-selected participants, similar to much of the recent literature (Kahn and Wolak 2013, Ito 2014, Jessoe and Rapson 2014). The study was performed in a heterogeneous neighborhood in a hot climate where many households were interested in solar energy and electric vehicles, so we certainly cannot claim external validity to all neighborhoods in the United States. Our experiment also compensates households to participate in the program, and thus it should not be interpreted as identical to a utility-run pricing program. Our findings should be viewed in light of these limitations as providing an useful "proof of concept" of interventions that have potential to reduce emissions and electric grid costs that future research with larger samples and in other locations could corroborate.

Indeed, although the results in our study lead us to focus on air conditioning use and electric vehicle charging, as smart homes become more widespread with greater automation of appliances, additional opportunities for emission reductions and cost reductions may arise. One could imagine consumers allowing a signal sent from the utility to electric vehicles to ramp charging up or down depending on the cost and carbon intensity of the electricity. Future work on these topics can leverage the findings of our analysis to provide deeper insights for manager and policymakers working at the intersection of business and climate change.

Acknowledgments

The authors are grateful for conversations and comments from seminar participants at Yale, University of California Berkeley, ETH Zurich, Georgia State, University of Colorado, Boulder, Georgetown University, Dartmouth College, Georgia Tech, RWI Essen, McMaster University, Western University, Hong Kong University of Science and Technology; Fudan University, Erasmus University, Indian School of Business, ACR Conference, Marketing Science Conference, and the AMA-Sheth Doctoral Consortium, as well as comments from many colleagues. The authors thank the anonymous reviewers, associate editor, and editors for thoughtful comments on an earlier draft of this manuscript. The authors also thank the staff at the Pecan Street, especially Grant Fisher.

Endnotes

[1] For more on the importance of shifting consumer demand in Texas to reduce what is commonly called "stress on the electric grid" during peak times, see https://www.texastribune.org/2022/05/13/texas-power-conservation-heat/.

[2] This is a concept Texas regulators are eager to spread; see https://www.texastribune.org/2012/08/01/texas-push-save-power-peak-times/.

[3] The installations were paid for by grant funding raised by Pecan Street and the budget only allowed for 280 houses to be included in the study.

[4] See Online Appendix B.3, Table B5, for further summary statistics on electricity consumption.

[5] To be clear, the triple differences are (1) control versus treated, (2) event day versus nonevent day, and (3) event period versus nonevent period (4 PM to 7 PM). The triple difference specification would include each of these variables independently, all two-way interactions between these variables (e.g., 1×2, 1×3, and 2×3),

and the interaction between all three, that is, the triple difference. However, our fixed effects absorb all the variables and most of their two-way interactions.

[6] One question this specification raises is whether there may be spillovers from event hours to non-event hours on an event day. When we drop the two hours prior to the event period and/or the two hours after the event period, it turns out this has very little effect on our estimates. See Table C1 in Online Appendix C.1 for details. We also explore other subsamples of the data, such as removing the day before and after a treatment day when one might be worried about spillovers. We find no perceptible differences in results.

[7] We perform several robustness checks to address standard error concerns. First, multiple hypothesis testing (MHT) is a potential concern in all empirical work, and occasionally economists have begun adjusting for it. The statistical significance stars in our tables are based on standard tests, but we also use the Bonferroni MHT correction procedure to adjust the p values in all of the models run in this paper and find very few changes. All of the statistically significant coefficients in the critical peak program remain statistically significant with little change in the stars. We lose somewhat more significance in the off-peak pricing treatment, but the off-peak treatment hour-specific results still show statistically significant treatment effects in some hours. Second, clustered standard errors may be somewhat conservative, so we also use Newey-West standard errors (with 60 lags based on the common $0.75 \times T_{(1/3)}$ rule of thumb, where T is the number of time periods). We find no notable changes in the statistical significance.

[8] The pricing treatment effect is statistically different from the information treatment effects with p values of 0.0000, 0.0002, and 0.0002 for the text, text with information, and portal treatments, respectively.

[9] By convention, our data are measured in kWh per minute, which is a rate. We could determine the total kWh used by each house by dividing use by 60 to get kWm per minute and summing across all minutes in the sample.

[10] The figure presents electricity consumption net of a house fixed effect to cleanly focus on the variation we are interested in between the treatment and control. In other words, we regress consumption on a household fixed effect and then predict consumption based on the constant and the residuals.

[11] Specifically, we perform two-sided t tests and cannot find a significant difference (even at the 10% level) for any hour for any of treatments. The closest is midday for the text with message treatment, but even this is not statistically significant.

[12] Adjustable uses include all monitored lights, bathroom use, bedroom use, clothes washer use, dryer use, dining room use, dishwasher use, kitchen use and kitchen appliance use, and office use.

[13] The results for the "unaccounted" electricity use are similar to those for the non-adjustable category, with no statistically significant effects (see Online Appendix C.1).

[14] Recall that off-peak prices were between 8 and 9 cents/kWh in 2013 to 2014.

[15] Table C6 in Online Appendix C.5 presents the results by hour.

[16] Online Appendix E provides model-free evidence also showing that the effect appears to be greater for electric vehicle owners.

[17] We assume 11,000,000 houses in Texas based on Census data in https://www.census.gov/ quickfacts/TX.

[18] F150 Average fuel efficiency 0.05 gallon/mile × 0.00889 tonnes CO2/gallon × Social Cost of Carbon 185$/tonne = $0.082/mile or the damages from driving a Ford F150 1 mile. Comparing to the avoided damages from the CPP $1,299/999/$0.082/mile=15,808,882 miles.

[19] There are 52,190 electric vehicles registered in Texas according to https://electrek.co/2021/08/24/current-ev-registrations-in-the-us-how-does-your-state-stack-up/. For this calculation, we simply take the nighttime treatment effect and multiply it by the marginal emissions during the non-nighttime hours (6 AM to 9 PM).

[20] The sources are https://www.ercot.com/gridinfo/load/load_hist/ and https://www.ercot.com/gridinfo/.

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