Field Experimental Evidence on the Effects of Information and Pricing on Residential Electricity Conservation*

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Abstract

This study examines how electric utilities and regulators can encourage residential consumers to conserve electricity during summer critical peak periods and shift electricity load from the day to off-peak, nighttime hours. We analyze a two-year field experiment in Texas exploring approaches to conservation and load-shifting in order to enable emission reductions and, in the near future, higher market shares of intermittent renewables. Our critical peak pricing intervention reduces electricity consumption by 14% on the peak hours of the hottest days, leading to CO_2 emission reductions of approximately 16% during these periods. Using unique high frequency appliance-level data, we can attribute 74% of this response to air conditioning. A complementary program that reduced nighttime, off-peak prices showed a significant consumer response and provided the first evidence of electric vehicle load-shifting in response to price. In a deep decarbonization simulation replacing fossil fuels with renewables,

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we show how pricing approaches can reduce the need for expensive energy storage or backup generation capacity.

Keywords: critical peak pricing, informational interventions, electric vehicles, load-shifting, habituation, spillovers.

1 Introduction

An important question among business leaders and policymakers is how to reduce greenhouse gas emissions at the lowest cost, thereby addressing climate change in a sustainable way and allowing for deeper emission reductions. In this paper, we focus on two important and related research questions, both of which are linked to the theme of business and climate change. We ask: "What are effective ways in which electric utilities and their regulators can encourage residential consumers to (i) conserve electricity during summer critical peak periods with the hottest temperatures, and (ii) shift electricity load from daytime hours to off-peak, nighttime hours?" Answering these two questions opens pathways for reducing air pollutant emissions and electricity generation costs, and facilitating high market shares of intermittent renewable generation, while keeping the lights on and maintaining affordability.

We address our questions in two stages. We begin by analyzing the results of a two-year field experiment in Austin, Texas with two programs of treatments: one in summer critical peak hours and one in shoulder-season off-peak hours.[1] Our results suggest (i) a decrease in air conditioning usage in response to critical peak pricing (CPP) that substantially raises the price of electricity during daytime critical peak hours and (ii) a shift in charging of electric vehicles from daytime hours to the night in response to lowered nighttime prices. Our research approach is in the spirit of field experiments that address questions relevant to management science (Li et al. 2015; Fisher et al. 2018; Zhang et al. 2020). In the second stage, we examine the implications of our results for the environment. We explore the impact on greenhouse gas emissions and other air pollutant emissions, as well as the effect on electricity generation costs, as lowered costs would enable the electrification of further end uses. We also perform a deep decarbonization simulation to show how low-cost experiments such as ours can enable high market shares of intermittent renewables while retaining reliable electricity supply.

Our paper relates to a growing literature that has demonstrated that consumers face

[1] In the nomenclature of Harrison and List (2004), our study is of a "framed field experiment."

information costs, such that the simple conveyance of information can change behavior. Consumers reduce their use of mobile phone minutes when told they are reaching the next pricing tier (Grubb and Osborne 2015), information on calorie counts can reduce caloric intake (Bollinger et al. 2011), information on the popularity of products can increase interest in products with narrow appeal (Tucker and Zhang 2011), and information on the the number of buyers and sellers in a market affects the number of listings on eBay (Tucker and Zhang 2010). Information provision interventions often aim to influence behavior based on pro-social motives, pecuniary motivations, or some combination. For instance, conservation appeals can reduce electricity use during times of crisis (Reiss and White 2008; Ito et al. 2018), while Brandon et al. (2018) and Allcott and Rogers (2014) show that social nudges can reduce electricity usage and Jessoe and Rapson (2014) shows that high-frequency electricity usage information increases price responsiveness during peak events. In our paper, we explore information interventions alongside CPP in our daytime peak hour treatment period.

Examining information treatments at the same time as pricing treatments is useful because policymakers are often drawn to information-based approaches as politically palatable ways to reduce residential electricity consumption during critical peak times. From a political feasibility perspective, such information-based approaches are advantageous in that they do not require changing prices, and customer adjustment costs are likely lower than under dynamic pricing approaches (Spector et al. 1995). However, dynamic pricing approaches, such as CPP or real-time pricing, more directly align retail prices with wholesale prices. But both information and pricing have the potential to allow demand to respond during times when the social cost of electricity provision is very different than the retail price.[2]

We design our field experiment and analysis to test a set of hypotheses stemming from our research questions. The summer program tests how information provision and conservation appeals compare to CPP during 27 of the hottest days over two summers,

[2]Researchers have been thinking about dynamic pricing of electricity for many years, with notable papers including Granger et al. (1979), Caves et al. (1984), Faruqui and Sergici (2010), and Allcott (2011*a*).

when the wholesale price of electricity is substantially above the retail tariff and dirtier generation is used to meet demand. The off-peak program tests for an asymmetric pricing response and load-shifting, especially by electric vehicles, by offering lower marginal prices of electricity during the night in off-peak months, when the wholesale price of electricity is below the standard retail tariff due to high production from West Texas wind facilities. Combined, these two programs provide a unique picture into how consumer demand can be adjusted to meet conditions on the electricity grid, which is likely to become ever more important with higher market shares of intermittent renewables on the grid.

A novel feature of this study is that we not only observe minute-level electricity consumption, but we also observe electricity consumption by key appliances, allowing us to show that a primary causal channel for the effect of CPP is from reducing air conditioning usage. During the nighttime off-peak pricing period, the appliance that is used most is the electric vehicle charger. Such appliance-specific results provide deeper insight into the mechanisms underpinning the consumer response interventions designed to improve environmental outcomes and economic efficiency.[3] One theme that emerges from our study is the importance of automation in electricity demand (Bollinger and Hartmann 2020). Consumers in our field experiment have programmable thermostats and can program their air conditioning use, and those that have electric vehicles can also program their charging. In contrast, many other appliances cannot currently be automated (although this may change with the advent of smart homes).

Our key results are as follows. First, we show that (i) the reduction in residential electricity usage is highest in our CPP treatment relative to any of the information treatments, (ii) this reduction is mainly attributed to a reduction in air conditioning usage (which is about 74% of the total response), (iii) the nighttime treatment shifts electricity consumption from daytime hours to nighttime hours, and (iv) the load shift to nighttime

[3]For those interested, there is an industry consultant report by the staff who assisted the on-the-ground running of our experiment (Zarnikau et al. 2015), which presents some descriptive figures of the raw data, but does not perform an analysis of causal impacts.

in our off-peak pricing experiment is due to charging of electric vehicles. Notably, we provide the first well-identified evidence of load-shifting from lower prices of electricity use at night,[4] and show that the source of this load shifting is largely from electric vehicle owners programming their vehicles to charge late at night. This result is new to the literature and holds promise for policies that aim to improve economic efficiency by lowering nighttime electricity prices because electricity cannot yet be stored on a large scale (Zhou et al. 2016). We also show that, when put in terms of elasticities, the response to the price decrease (price elasticity=-0.28 (95% CI={-0.58,0.02})) appears to be greater than the response to the increase (price elasticity=-0.03 (95% CI={-0.06,-0.02})). We speculate that this is because a greater fraction of the nighttime electricity load is programmable electric vehicle charging. It may also be because of the ease of shifting electric vehicle charging to later at night in contrast to the discomfort engendered from reducing air conditioning.

In the second stage of our analysis, we explore what the results of our field experiments mean for emissions. We calculate that for each of the 27 CPP events, the average reduction in carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) 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 $773,000 per event based on social cost estimates. The nighttime treatment leads to an increase in electricity generation at night. The marginal generator in Texas during the nighttime is coal, so emissions actually increase on net in response to the electric vehicle load-shifting from largely natural gas marginal generation during the day to coal generation at night. We expect this load-shifting result will change in a more deeply decarbonized system run with high levels of nighttime wind generation (possibly being curtailed) and/or sufficient battery storage. Moreover, even though the nighttime program increased emissions, the increased social cost of the additional emissions ($13,405) is lower than the associated reduction in generation cost due to the much lower wholesale electricity prices at night ($26,157). Thus, if there is no change in consumer surplus

[4]There is well-identified evidence on load shifting to the off-peak outside of electricity, such as in telecommunications (Malone et al. 2017).

(a plausible assumption in this case due to the ease of programming electric vehicles to charge at night), then the nighttime pricing would have positive social net benefits.

Building on these results, we develop an illustrative deep decarbonization simulation where we replace all fossil fuel generation in the 2020 Texas electricity grid with wind and solar generation. Keeping the lights on in this deep decarbonization thought experiment could be achieved with large-scale energy storage (e.g., batteries), backup fossil fuel generation, or even more renewables that will be curtailed much of the time (more transmission connections may be helpful too). All of these are expensive. We show that allowing for responsive demand through CPP applied broadly can reduce the need for battery capacity by 53%. And if battery storage is not an option, CPP could substantially reduce the cost of generation needed to keep the lights on in the deeper decarbonization scenario, with savings as high as $1,000 per hour for the average generation cost and $15,000 per hour for the maximum generation cost.

The results of this study have several managerial and policy implications. Besides suggesting that information-only interventions are less effective than pricing interventions during typical summer peak periods, they also provide new evidence of the effectiveness of reducing electricity prices during low wholesale price periods on consumer demand. We are unaware of previous work that evaluates the effect of changes in nighttime electricity prices, and the degree of load-shifting we observe demonstrates the effectiveness of this pricing policy. Given that 74% of the total response to critical peak pricing comes from air conditioning, an alternative approach to critical peak pricing is to have households enrolled in automatic control of air conditioning by the utility during critical peak periods (a next step in automation), which would bring in a large fraction of the gains from critical peak pricing. This is an important result that would not have been possible without empirically analyzing appliance-level data. Our study is also among the first to quantify the significant reduction in greenhouse gas emissions based on experimental evidence in residential electricity conservation from pricing.

One key aspect of the field experiment is that it was conducted in a setting with a relatively high penetration of electric vehicles, and thus provides some foresight into a likely future in which the transportation sector and electricity grid are more closely interlinked. This aspect also implies that some of the results, such as the off-peak lower-pricing results, should not be directly applied to other neighborhoods today with much lower penetration of electric vehicles, but will become increasingly relevant in the near future (Sebastian 2021). We believe that our CPP results provide useful insights for understanding consumer behavior in similar neighborhoods throughout the South and Southwestern United States with similar hot days as in Austin, while they are less useful for areas with different climates and households.

The paper proceeds as follows. In the next section, we discuss the design of our field experiment and hypotheses based on the literature. Section 3 presents the data, econometric analysis, along with descriptive model-free evidence of the treatment effects. Section 4 discusses implications for air pollutant emissions and generation costs, and section 5 presents a decarbonization simulation. Section 6 concludes.

2 Research Design and Hypotheses

2.1 Design of the Field Experiment

The two programs of our field experiment were conducted in 2013 and 2014 in Austin, Texas. The non-profit "Pecan Street Inc." is our partner and data provider.[5] Pecan Street has developed relationships with hundreds of households within the Mueller neighborhood of Austin, Texas to monitor their energy use, much as a utility would monitor energy use.

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 Ap-

[5] Pecan Street is an Austin-based non-profit affiliated with UT-Austin founded in 2008 dedicated to building a deeper understanding of energy and water use through systematic monitoring and measuring of consumption behavior. See https://www.pecanstreet.org/about/ for more details on Pecan Street.

pendix A for the e-mail 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. Thus, this study is akin to nearly all of the recent field experiments on electricity consumption in being a randomized controlled trial for self-selected participants (e.g., Wolak (2013, 2011); Jessoe and Rapson (2014); Ito et al. (2018)). As such, our research design assures internal validity of the study and we carefully discuss the external validity of the study for proper interpretation of the findings.

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 for 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). 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.[6]

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 4PM to 7PM."

4. Active Information + Recommendation - 46 homes received the same text message

[6]Each participant had access to an online portal. For the portal treatment group, this was the only treatment. The portal displayed monthly whole home energy use in kWh, monthly energy costs in dollars per appliance, energy generation cost in dollars if the participant had solar panels, real-time energy consumption in kWh, monthly energy cost comparison to other participants within the same zip code, and monthly energy usage trends.

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 4PM-7PM. 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.[7]

For the average customer, the Austin Energy summer (June-September) electric rate in 2013 was 11.4 cents/kWh and in 2014 was 12.1 cents/kWh. 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.[8] 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 (i.e., the information groups and the pricing group) were sent an e-mail upon their registration indicating that they could save money during peak times by shifting laundry, dishwashing, and air conditioning usage 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

[7]The pricing group received a text message one day prior to the beginning of each nighttime off-peak pricing month.

[8]Online Appendix A.1 includes more details on the Austin Energy rates and experimental rates.

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 marginal price for consumers, 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. Household receive their usual electric bill from Austin Energy, but will also receive 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 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.[9]

We recognize that 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 e-mail 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).[10]

Due to 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

[9]We explored whether the response to the CPP tariffs varies with the credit balance and did not find much of interest.

[10]Note that the payment was not until after the treatment and generally participants in the experiment are reasonably well-off, so do not anticipate weak separability with the level of income being violated.

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 minor 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. While it is always impossible to fully rule out site selection bias without performing multiple studies, the additional 24 households included from outside the Mueller neighborhood provide some further evidence on the external validity to the rest of Austin. We are very cautious in extrapolating our results too far beyond Austin, but believe that they provide useful information on other settings in the south and southwestern parts of the United States that have similar climates and demographics (e.g., certain neighborhoods in Albuquerque, San Antonio, Dallas, etc.).

2.2 Hypotheses

Our primary focus is to determine effective ways that utilities can encourage residential consumers to conserve electricity during critical peak periods, shift electricity demand from daytime hours to nighttime hours, and reduce emissions and generation costs. Based on prior literature, there are several ways to reduce residential electricity consumption during peak periods and influence consumer behavior: (1) Information provision can be effective through an in-home device that give households real-time feedback on electricity consumption or access to an online portal (Martin and Rivers 2018; Asensio and Delmas 2015; Bollinger and Hartmann 2020), but it could also lead to an information overload (Bettman et al. 1998; Chen et al. 2009). (2) Text message conservation appeals, focusing on intrinsic motivation, may be especially effective for energy conservation during crisis periods such as in Japan during the Fukushima Daiichi nuclear crises (Ito et al. 2018) and during the California electricity crisis (Reiss and White 2008). (3) Social norm messages along with suggested concrete actions based on OPower Home Energy Reports and WaterSmart Reports have been modestly effective in several settings (Ayres et al. 2013; Brandon et al. 2018; Ferraro and Price 2013; Allcott 2011*b*). Finally, (4) CPP has been shown to be effective at inducing energy conservation, although the price response may be quite inelastic, especially without automation (Bollinger and Hartmann 2020; Gillian 2018; Jessoe and Rapson 2014; Ito et al. 2018; Prest 2018; Wolak 2006). Thus, with respect to critical peak events on regular summer days (rather than times of crisis) that go to consumers who have access to at least some automation technologies, our hypotheses are two-fold:

H1a: We expect to see a reduction in electricity use from our CPP treatment and this effect will be larger than the effect from information.

On hot summer days we expect air conditioning usage to dominate residential electricity demand, and air conditioning can be programmed in advance in our empirical setting. Thus, we conjecture that air conditioning will be more responsive to changes in peak period electricity prices than the demand from other appliances. Prior research in residential electricity conservation has not had appliance-level data, and thus this is one of the key contributions of our paper. These data allows us to deepen our understanding of air conditioning as the primary contributor to demand reductions, and therefore emissions reductions, and ultimately the effectiveness of regulatory and policy instruments to mitigate the impact. We now offer our second hypothesis:

H1b: We expect to see a significant reduction in air conditioning usage from our CPP experiment, and this effect will be the largest relative to the other individually-metered appliances. Such a reduction in air conditioning usage will be associated with air pollution emission reductions.

While there is some evidence available on CPP, there is little available evidence to inform hypotheses about our nighttime, off-peak program both in terms of how load can be shifted as well as the appliances that are most impacted by off-peak pricing programs. Of course, electricity use at night is different than electricity use in the day. With nearly all appliances either off or running all the time (such as refrigerators), one might expect a very inelastic response at night. Yet most previous studies did not involve homes with programmable thermostats and electric vehicles that can be programmed to charge at different times. Harding and Lamarche (2016) find load shifting from households with programmable thermostats, suggesting that we might expect to see some changes in electricity use, especially from electric vehicle charging, which is very easy to program to automatically complete charging by a certain time. Thus, we offer the following three-part hypothesis:

H2a: The low-price nighttime treatment will lead to load shifting from daylight hours to nighttime hours, improving overall economic efficiency by reducing generation costs.

Given that many households in our study have electric vehicles, we offer the following hypothesis:

H2b: We expect a load shift in electric vehicle charging from peak times to off-peak times in response to the off-peak, nighttime pricing.

Further, due to the ease of setting an automatic schedule for electric vehicle charging, more non-programmable appliances in use anyway during peak hours than at night (e.g., cooking, computers), and discomfort costs associated with giving up air conditioning, we suggest the following:

H2c: The price decrease during off-peak hours should lead to a stronger response than the price increase during critical peak periods.

3 Data, Econometric Analysis, and Results

3.1 Data

The primary outcome variable is electricity consumption. We have unique minute-appliance-level electricity consumption data for each household from March 2013 through October 2014.[11] 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 dataset. 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), non-summer (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, clothes washing and drying, etc. In non-summer periods, this is just under 40% of electricity consumption 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 above, 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 over 50% of consumption, as might be expected due to the many small appliances in a typical house hold (e.g., computers, phone chargers, hair dryers, electric tools, etc.). In summer periods, this drops to 37% and in event periods it drops further to 23%. The three

[11] Asensio and Delmas (2015) is the only other paper we are aware of using minute-appliance-level electricity consumption data for a large sample of households; however, their sample consists of UCLA students in a housing complex, rather than the residents of a neighborhood.

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 for 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 constitutes 16% of electricity use, while in the summer months it constitutes 45% of electricity use, and during event days it reaches 63% of 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 36% of households in the pricing and treatment groups that have electric vehicles, the percentage of electric vehicle electricity consumption (by minute) is 5.7%.

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, all observables are not statistically different between the control and treatment groups at a 5% significance level. The minor differences across groups in some of the observables–due simply to random variation–motivate our empirical strategy and further robustness checks. Row 1 of Table 2 indicates there is no statistical difference between treatment and control group non-event day electricity use, which is a useful placebo test for the randomization.[12]

[12]See Online Appendix B.3 Table A.7 for further summary statistics on electricity consumption.

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:

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

where Y_{it} is the electricity usage 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). ρ_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.[13] $\mathbf{X}$ 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).[14]

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 non-peak days, and across treatment and non-treatment hours. 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).[15]

[13] We thank Severin Borenstein for suggesting quarter-hour fixed effects.

[14] To be clear, the triple differences are 1) control versus treated, 2) event day versus non-event day, and 3) event period versus non-event period (4PM-7PM). The triple difference specification would include each of these variables independently, all two-way interactions between these variables (e.g., 1X2, 1X3, and 2X3), and the interaction between all three, i.e., the triple difference. However, our fixed effects absorb all the variables and most of their two-way interactions.

[15] 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

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 A.9 in the Online Appendix D.1 for details.[16]

Column (1) in Table 3 presents our raw results without any household or time fixed effects. That is, for all but the pricing treatment, there is very little difference in electricity consumption between the treatment and control. Looking at the mean during the treatment period, this amounts to about a 20% reduction in usage. 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. These coefficients are also close to zero, consistent with our Hypothesis H1a and similar to Column (1).[17]

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 95% confidence interval (CI = {-0.586,-0.194}). The 95% confidence intervals of the text message and portal treatments do not overlap with the pricing treatment. These results suggest that it is quite unlikely that the information treatments provide a similar effect as the pricing.

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, just as in the raw data.[18] For comparison, this decline in elec-

significance in the off-peak pricing treatment, but the off-peak treatment hour-specific results still show statistically significant treatment effects in some hours.

[16]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.

[17]Clustered standard errors may be somewhat conservative, so we also use Newey-West standard errors (with 60 lags based on the common $0.75 * T^{(1/3)}$ rule of thumb, where T is the number of time periods). We find no notable changes in the statistical significance.

[18]By convention, our data is measured in kWh per minute, which is a rate. We could determine the

tricity consumption is equivalent to $0.75 per event or $20.22 across the 27 event periods.

We now examine model-free evidence of the treatment effect to visually demonstrate the effects seen in Table 3. We begin with non-event days for a baseline. Figure 1 presents electricity usage by minute on average for all non-event days in our sample stratified by treatment group. Each figure shows the control group and one of the treatment groups. Panel (a) shows usage for the portal group, Panel (b) for the text message group, Panel (c) for the text message and suggested action group, and Panel (d) for the pricing group.[19] For reference, the event day treatment period is shown by the shaded areas, although these figures cover only non-event days, i.e., there is no treatment occurring. For each of the panels in Figure 1 there is no clear difference between the treatment and control. We also perform a series of statistical tests, and cannot find an hour of the day where there is a significant difference between the treatment and control.[20] This further reassures us that our randomization is successful with respect to the factors that influence electricity use.

Figure 2 presents the same figures for critical peak event days only, providing descriptive evidence of the treatment effect. Again, there are four panels, each representing one of the four treatments. A first clear finding from Figure 2 is that for all but the pricing treatment, there is very little difference in electricity consumption between the treatment and control. This is true both during treatment hours and in non-treatment hours. However, for the pricing treatment (Panel (d)), we see a large reduction in electricity usage during the treatment hours.

We now turn from the overall treatment effect results to the 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 re-

total kWh used by each house by dividing use by 60 to get kWminute per minute and summing across all minutes in the sample.

[19] All panels present 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.

[20] Specifically, we perform two-sided t-tests, and cannot find a significant difference (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.

duction in electricity consumption from adjustable uses across treatments is very similar to the total reduction in column (1).[21] Again, we see no statistically significant effect for any of the information treatments. 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 the results for non-adjustable uses, and it shows no statistically significant effects for any of the treatments, as would be expected by definition of this category of uses.[22]

Column (5) of Table 3 focuses on what we find to be the most important electricity use: 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, so one might expect much of the response to be from this use. Indeed, the results in column (5) show a reduction of 0.29 kWh per minute from air conditioning usage alone for the pricing treatment group. This result, along with the result for all electricity use, suggests that air conditioning makes up 74% of the reductions in electricity use, a slightly greater percentage than the percentage of electricity use from air conditioning on event days. This provides support for Hypothesis H1b and we will further examine its implications for decarbonization in the next section.

Figure 3 visually presents the treatment effect on air conditioning use on event days. What is key about this figure is that it almost exactly mirrors Panel (d) of Figure 2. The treatment group and control group air conditioning use appears to follow a nearly identical trend prior to the treatment period, followed by a large decline in the treatment group air conditioning use during the treatment period, and this decline extends for approximately two hours after the treatment period. This model-free evidence aligns with our regressions in highlighting that air conditioning is playing a key role in the electricity reductions in the pricing treatment.

Online Appendix D.1 presents the results for other major electricity uses, including

[21] 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.

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

use from electric vehicles and unaccounted-for uses. For several other major uses, including electric vehicles, we find no significant effects despite the large number of observations. We view these results as indicating that the non-air conditioning reductions stem from many different electricity uses, with no single other use dominating. As before, the information treatment groups show no statistically significant treatment effects. These findings highlight the importance of programmable air conditioning for the response to critical peak pricing in hot climates like in Austin, Texas.

Researchers and policy makers are often interested in calculating the price elasticity of demand for electricity use. In our context, it is possible to calculate the price elasticity at the mean consumption level for the pricing group. For overall electricity use, the price elasticity of demand is -0.03 (95% CI={-0.06,-0.02}) and for air conditioning use only it is again -0.03. However, we view these elasticities very cautiously. There is evidence from two recent papers that the price elasticity of electricity use during critical peak pricing or time-of-use pricing may vary with the level of the price change (Gillian 2018; Prest 2018). Thus, we interpret our -0.03 elasticity as the price elasticity of electricity consumption for the roughly \$0.64 - \$0.12 = \$0.52 per kWh change in effective marginal price in our study, and our results do not speak to how the price elasticity might differ for different marginal price changes. However, this price elasticity of -0.03 is slightly smaller in magnitude than the commonly estimated elasticity of -0.1 (e.g., Ito 2014).

We perform a series of robustness checks to confirm the above results (See Online Appendix D.1 for details). For example, we exploit different sources of variation and find that our results are quite robust. We also examine the results using 15-minute-level data instead of minute-level data, and find nearly identical results. We further examine the behavior of the pricing treatment group on non-event hot days above 90 degrees F to confirm that households are responding to pricing and not just the hot day. We were surprised to see a minimal effect from the information treatments. We find that consumers do not significantly respond to information alone during normal peak period events. One possible reason we might see this result is that the households in the sample were already aware of the critical peak days and were very conservation-minded. If this was the case, we would expect to see a difference in the control group between critical peak days and similar very hot days over 90 degrees. We do not see any difference, ruling out this explanation.

We next explore a robustness check where we replace the control group in our estimations with a control group of 24 households elsewhere in Austin. We find similar results (see Table A.9). 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 remain consistent (see Online Appendix D.2). For more tests on further evidence on mechanisms, see Online Appendices D.3 and D.4 where we examine evidence of pre-cooling and whether households are actually home during the event periods. It turns out that in general, households did not pre-cool their homes and that people did not leave their homes due to the high price event. In Online Appendix D.5 and D.6 (Tables A.15 and A.17) we test for spillovers and habituation in the pricing treatment where the coefficients on the post-event period dummies are statistically significant, consistent with the model-free evidence in Figure 2, i.e., households being slow to turn their air conditioners back on just after the end of the event period, in contrast to the load-shifting leading to increasing electricity usage found in Harding and Lamarche (2016). We also find that there is still a reduction in electricity use even at the end of the second year (Table A.17). To the best of our knowledge, these findings about habituation and continued long-run reductions from critical peak pricing are new to the literature, a finding that is only possible due to our research design that covers multiple years.

We conducted additional robustness checks (see Online Appendices D.5 and E) as follows: (i) examining hourly treatment effects (Table A.16), (ii) exploring heterogeneous treatment effects where each demographic variable (house square feet, preferred temperature, presence of solar photovoltaic panels, programmable thermostat, education, income, number of residents, and number of televisions) is interacted with all triple difference variables (Tables A.18 and A.19), and (iii) treatment effects by usage tiers (Table A.20). We find that our results continue to hold, thus showing the robustness of our results.

3.3 Nighttime Off-Peak Pricing Treatment Effects

Our field experiment complements the summer pricing program with our off-peak night program, where 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 10PM to 6AM is $0.0265 per kWh for that month.[23] As mentioned above, it is straighforward to program electric vehicles to be finished charging by a certain hour, so we run our analysis on all electricity use and electricity used for charging by electric vehicle owners.

We begin our econometric analysis by examining the effect during daytime hours versus nighttime hours. Here we only include households in the pricing treatment and control group and we only include the off-peak months in our sample. We estimate the following linear specification:

$$Y_{it} = \sum_{h} \beta^h T_{iht} + \rho_i + \phi(t) + u_{it}, \tag{2}$$

where Y_{it} is again electricity usage 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 10PM-6AM (or an average over several of the hours). As before, ρ_i are household fixed effects, and $\phi(t)$ are fixed effects for each 15-minute interval in the sample.

For ease of presentation, in Table 4 we present coefficients for two four-hour time frames of night hours: 10PM-2AM and 2AM-6AM.[24] The choice of these time frames was motivated by Figure 4. Column (1) presents the results for all electricity uses, column (2)

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

[24] Table A.14 in Online Appendix D.5 presents the results by hour.

for electric vehicles, and column (3) for heating. Figure 4 provides model-free descriptive evidence of the substantial load-shifting from daytime hours to night hours for total electricity use and electric vehicle charging use, visually illustrating the results in Table 4.

Consistent with H2a, we find an average increase in total electricity consumption in the 2AM-6AM off-peak hours of 0.13 kWh per hour (p-value < 0.1). 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 3AM and 4AM, we see an increase of 0.19 kWh per hour (p-value < 0.05). There is also a statistically significant effect for the hours 2AM-3AM that is similar in magnitude to the effect for 3AM-4AM. Table 4 also shows the results for electric vehicles (column (2)) and heating (column (3)). 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 great potential for managing nighttime electricity load, supporting H2b.[25] As electric vehicles become more common, this finding suggests that nighttime low pricing will be increasingly valuable to improve economic efficiency by encouraging households to shift the charging of electric vehicles to low-cost hours. With "vehicle-to-grid" use of electric vehicle batteries for grid management, it is possible that the potential to improve economic efficiency will be even larger in the future.

The heating results in column (3) are not statistically significant and are close to zero. This suggests that electric vehicle charging is the primary driver of our off-peak nighttime treatment results. Since electric vehicles can be automatically set to complete charging by a certain hour, households that respond to the off-peak treatment by adjusting their charging schedules do not face any physical discomfort, unlike what they face when they turn down air conditioning during peak summer periods. This may explain why we find households to be more responsive to an off-peak price reduction than a price increase during critical peak periods.

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

These estimates correspond to an elasticity of -0.28 (95% CI={-0.58,0.02}), indicating that when prices at night go down by 10%, electricity usage increases by 2.8% on average. This is a greater response than to CPP, suggesting an asymmetric response and supporting H2c. This asymmetric response is likely due to the ease of automating electric vehicle usage in the night hours, but we cannot rule out other possibilities, such as reference dependent preferences where consumers respond differently to prices increases than decreases (Briesch et al. 1997; Greenleaf 1995; Winer 1986). Of course, the same caveats as in the daytime treatments about interpreting our responses as elasticities still hold, in that the response may be to having any price decline, rather than to having the specific price decline in this experiment.

We should add the caveat that the randomization was not performed over electric vehicle ownership, and Table 2 showed a difference between the treatment and control in the fraction of households owning electric vehicles. This may lead to a concern about sample selection in these results, so we perform two robustness checks in columns 4 and 5 of Table 4 (see also Table A.14). First, we use a larger control group that also includes the control homes from elsewhere in Austin. This brings the fraction of electric vehicles in the control group to 34%. The results are in Table 4 column 4 and are comparable to our primary results. Next we use a matching estimator, where we match on pre-treatment electric vehicle usage (see Online Appendix D.5 for details). Table 4 column 5 shows that the results are again similar.

4 Emissions and Generation Costs

We now turn to the implications of our results for emissions and generation cost savings. We bring together data on marginal emissions and the marginal costs of generation at the hourly level, which we then apply to our treatment effects.

We first examine the effects on emissions. We estimate marginal emissions following Holland et al. (2016) for ERCOT between 2013-2014. Table A.16, A.17, and A.18 display the results of regressing total CO_2, SO_2, and NO_x emissions on hourly load for our event periods only, for all summer peak periods (4PM-7PM), and nighttime hours (10PM-6AM). The results indicate that marginal emissions are generally lower during peak periods than other times of the day and marginal emissions are higher at night. These results are unsurprising as the marginal fuel is natural gas during the peak periods whereas the baseload fuel is often coal. Tables A.19 and A.20 display the marginal emissions calculations for 2019, for reference.

Table 5 displays our emissions calculations.[26] Panel A displays the daily emissions reductions associated with the CPP treatment effect. We apply the treatment effect to the three CPP hours (4PM-7PM) and extrapolate the results to all residential households in Texas.[27] We find that if all houses in Texas received the CPP treatment, we would see an average reduction in CO_2, SO_2, and NO_x emissions of 7,027 tons, 7,542 lbs, and 10,720 lbs respectively. Using a $50/ton social cost of carbon, 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 $351,351, $346,923, and $75,044 per CPP event period for each pollutant respectively. Panel A also displays the social benefits of the CPP on air conditioning alone. On average the air conditioning benefits are approximately 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.[28] This not only connects our results more closely to climate change, but also provides a nice comparison of the emission effects of our treatments to the average emissions of peak period electricity use. Of course, decarbonization of the electricity system may occur at the same time as the climate warms, so these results should be seen as a "what if" scenario for climate warming with the electricity system remaining the same as today. We construct the difference between the preferred thermostat setting for a subset of homes and maximum daily temperatures in Austin and then we use this variable to

[26]See Online Appendix F for a detailed description of our emissions calculations.
[27]We assume 11,000,000 houses in Texas based on Census data in `https://www.census.gov/quickfacts/TX`.
[28]We thank an anonymous referee for this suggestion.

estimate the electricity required to cool a home as outdoor temperatures increase during the summer months (see Online Appendix E for further details). Table A.26 shows that a one °F increase in the outdoor temperature above the preferred indoor thermostat setting increases electricity and air conditioning use by 0.035 and 0.029 kWh per minute for the average sized house during the peak hours (columns 3 and 4). Based on these results, Panel B of Table 5 displays the additional cooling emissions associated with 1 °F and 3 °F increases in maximum temperatures above preferred thermostat settings, if this climate change occurs with the same electricity system as today. The 3 °F increase is about 40% of what can be saved from our CPP treatment.

Panel C of Table 6 displays the additional emissions and social costs of these emissions associated with the increase in electricity use caused by the nighttime off-peak treatment. The first row displays the additional emissions associated with the treatment effect extrapolated to all registered electric vehicles in Texas for one day.[29] The second row displays the emissions if these vehicles were charged during the day for comparison. To get this value, we simply take the nighttime treatment effect and multiply it by the marginal emissions during the non-nighttime hours (6AM-9PM). The third row displays the increase in emissions from the change in charging profile extrapolated to the entire treatment period (Nov-Dec and March-May). Finally, the last row of Panel C shows the social costs of these additional emissions, which are modest ($13,405 total across the three pollutants).

We now turn to generation costs. We use data on the hourly load and net generation by fuel type (wind, solar, coal, natural gas, nuclear, etc.) from the independent system operator on the Texas grid, ERCOT, for 2013-2020.[30] Net generation is reported every 15 minutes, which we aggregate to the hourly level. Hourly system lambda, an estimate of the hourly marginal costs are obtained from Federal Energy Regulation Commission (FERC) Form 714. Average hourly system lambda values for the CPP event days, for the

[29] 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/.

[30] The sources are http://www.ercot.com/gridinfo/load/load_hist/ and http://www.ercot.com/gridinfo/.

summer, and for the winter are reported in Table A.22.

Table 6 displays our calculations for the marginal generation costs. Panel A of Table 6 uses the system lambda values in Table A.22 to determine the reduction in generation costs associated with the CPP treatment effect for one house per event period in the first row and for all houses in Texas per event period in the second row. To do so, we multiply the marginal costs in \$/kWh by the CPP treatment effect multiplied by three hours. This produces a reduction in generation costs of \$0.059 per house per treatment period or \$652,419 if all houses in Texas received the treatment. Panel B displays the additional generation costs associated with warmer outdoor temperatures, as is possible with climate change. We observe that a 3 °F increase in temperature above preferred thermostat settings increases generation costs by \$175,651 per summer evening across all houses in Texas.

Panel C of Table 6 displays the reduced generation costs associated with the nighttime treatment effect. The first row displays the generation costs of charging one EV between 1AM-5AM, the second row extrapolates this to all EVs in Texas across the entire treatment period, the third row displays the generation costs of charging one EV between 6AM-9PM, and the fourth row extrapolates this to all EVs in Texas across the entire treatment period. The final row in Panel C displays the reduction in generation costs from the nighttime treatment period (\$26,157 across all EVs for the entire treatment period). In summary, the load shifting from the lower nighttime prices resulted in incremental emissions increases of 52.92 tons of CO_2, 232 lbs of SO_2, and 12.21 lbs of NO_x over a five month period across all registered electric vehicles in Texas. However, the increased social cost is much lower (\$13,405) than the associated reduction in generation costs from charging electric vehicles at night (\$26,157).

5 Deep Decarbonization Simulation

We complete our analysis with a deep decarbonization simulation. The idea behind this simulation is to explore what our econometric results imply as we progress towards very high market shares of wind and solar, which are inherently intermittent technologies.. We first consider what would happen if all of the fossil fuel capacity in 2020 was replaced with wind and solar. We explore a case with both the same fraction of wind and solar as in 2020, as well as cases with different mixes with wind and solar to minimize the production deficit from the loss of the fossil fuel capacity. This allows us to calculate the production deficit at different times due to the intermittency of renewables to show how load conservation or load shifting could help make up for this shortfall. Without load conservation or load shifting, grid operators would have to rely upon fossil fuel backup generation, even more intermittent renewable generation capacity in different locations, and/or energy storage (e.g., batteries) to ensure that the lights stay on (unless there was plenty of transmission capacity to other regions, which there is not currently for ERCOT). So, we also calculate just how much battery storage would be required to emphasize how large the cost savings may be, since while batteries are quickly dropping in price, they are likely to remain relatively costly for grid backup in the near future.[31]

For this simulation (details in Appendix F.2), we gather the following data from ERCOT: monthly generator-level coal and natural gas expenditures, total energy input in million Btus (MMBtu), and total electricity produced in MWh for 2013-2020. We also obtain generator-level hourly emissions from the Environmental Protection Agencys Continuous Emissions Monitoring System (CEMS).[32] We construct the heat rate (i.e., total energy input (MMBtu)/total electricity output (MWh) from the ERCOT data, and multiply the heat rate by fuel expenditures to get an estimate of each generator's variable cost in $/MWh. We combine this with each generator's nameplate capacity data from EIA Form 860 to construct simulated monthly supply curves for ERCOT.[33]

We begin our results by considering shutting down all coal and natural gas generation. Figure A.7 displays what would happen by quantifying the difference between the actual

[31]See Online Appendix F.2 for details.

[32]`https://www.eia.gov/electricity/data/emissions/`

[33]The mean variable cost in the data is $38.32/MWh with a minimum of $15.21/MWh and a maximum of $239.07/MWh. As an example of the simulated supply curves, we show the March 2013 supply curve in Figure A.6.

hourly fossil fuel generation and wind and solar generation on average in 2020. This shows the shortfall that would have to be made up with additional renewables.[34] It may be possible to optimize the mix of wind and solar to better match the shortfall, as the 2020 mix is certainly not optimized. Figure A.9 shows what the shortfall looks like in each hour of the day (on average) if wind and solar capacity is scaled up to exactly replace fossil generation capacity.[35] Some hours have a surplus, while others, such as the peak evening demand, experience large shortfalls (up to nearly 20,000 MWh). This underscores the high value of CPP during those hours for keeping the lights on in a deeper decarbonized electricity system. Furthermore, these results do not account for occasional longer periods that have low renewables generation (e.g., a week of cloudy, calm weather), and pricing may be very useful to reduce electricity load during these periods too. Moreover, if there is a 'duck curve' from a high market share of rooftop solar leading to a need for a fast ramping of generation in the morning and evening hours, pricing demand during these critical hours could also be beneficial to the grid.

The lights could also be kept on with plentiful battery storage, building additional renewables, or keeping fossil fuel plants around as backup. All three are likely to be expensive propositions and the latter would prevent deeper decarbonization. We calculate how residential CPP could help by applying the CPP treatment effect (in percentage terms) to residential load and subtract this from the deficit during hours with a shortfall. We find that CPP could make a dramatic difference in the deficits, especially with 40% wind or 50% wind in the renewables mix. For example, with 40% wind, the average daily shortfall would drop from 53,431 MWh to 8,315 MWh across all of ERCOT (see Online Appendix E Table A.28). In all cases, the generation deficit is much reduced (or turned to a surplus) with CPP, demonstrating the usefulness of CPP in reducing the amount of expensive battery storage or backup fossil generation needed. Online Appendix E Tables A.29 and A.30 calculate the average daily need for backup battery storage (or backup

[34] Figure A.8 displays the average wind and solar utilization rates per hour in 2020.

[35] To calculate the numbers in this figure, we scale up renewable capacity to exactly equal fossil generation capacity, divide it into fractions of wind and solar, multiply by the actual hourly utilization rates, and subtract the result from hourly fossil fuel generation.

fossil generation) and the maximum daily need for backup battery storage to keep the lights on. Both show that CPP can avoid the need to hold on the order of 2-3 GW backup capacity (a 53% decrease) to ensure the lights stay on. The markets for such capacity are limited, so finding an exact cost of this is difficult, but it is surely in the many millions of dollars. For example, using a simulated supply curve for 2020, the average and maximum generation cost saved by CPP could be as high as $1,000 per hour and $15,000 per hour, respectively, and this is likely a lower bound on the costs. Moreover, if pricing can be used to reduce electricity load during occasional longer periods of low generation, the savings are likely to be even greater.

6 Conclusions

This paper is about inducing electricity load reductions and load shifting to reduce emissions, improve economic efficiency, and enable greater market shares of intermittent renewables at a lower cost. At the core of the paper is a two-year field experiment with two complementary programs designed to induce a household response to changes in the marginal cost of electricity or changes in information. The first program increases the marginal cost of electricity during summer peak event hours and also tests several information programs designed based on the academic literature. The second program reduces the marginal cost of electricity during nighttime off-peak times when there is lower load and abundant wind generation in Texas that drives the wholesale price of electricity down. Both are designed to improve economic efficiency by more closely aligning the retail price with the social cost of electricity provision. We also use our unique appliance-level data to provide the first evidence we are aware of on the large contribution of air conditioning to the critical peak pricing response.

We show that (i) the reduction in residential electricity usage is highest in our CPP treatment relative to any of the information treatments, (ii) this reduction is mainly attributed to a reduction in air conditioning usage, (iii) the nighttime lower-price treatment successfully shifts electricity consumption from daytime hours to nighttime hours, and

(iv) this load shift to the night is due to charging of electric vehicles. A theme that runs through these results is that automation allows for greater responses, as air conditioning temperature settings and electric vehicle charging can be readily programmed. We also show that the response (quantified in the elasticity) to the nighttime price decrease is greater than to the CPP price increase, likely due to the ease of automating nighttime charging of electric vehicle charging and the personal discomfort that comes about with reduced air conditioning. This finding suggests that even when there is automation, consumers trade off the cost savings from adjusting to the prices against any loss in utility from discomfort. 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. We show that *each* CPP event will reduce emissions of CO_2, SO_2, and NO_x by 7,027 tons, 7,542 lbs, and 10,720 lbs respectively (approximately \$696,000 in avoided damages) in Texas. The nighttime program led to load shifting to the much lower-priced night hours. Currently, the marginal generation in the night hours is predominately coal, so the nighttime program increased emissions, but in a decarbonized system the marginal generation could easily be wind or batteries. Even though the nigthttime program increased emissions, the increased social cost of the additional emissions (\$13,405) is lower than the associated reduction in generation cost due to the much lower wholesale electricity prices at night (\$26,157).

We directly link our results to climate change mitigation with a deep decarbonization simulation that explores a shift from fossil fuels to renewables on the ERCOT grid. We show that there would be several times of the day that routinely would face a shortfall in electricity generation to meet the load in a renewables-only grid. Filling that gap is likely to be an expensive proposition, requiring plentiful energy storage, fossil fuel backup generation, and/or much more renewable energy capacity in many different locations. Our results show that the need for battery capacity in Texas in this deep decarbonization simulation would be over 4 GW if only battery capacity is used, but if we apply our results from the CPP, then the need for battery capacity would drop by 53%. And if battery storage is not an option and fossil generation is used, we show that the savings from the CPP could be as high as $1,000 per hour and $15,000 per hour, respectively. These results are likely to be underestimates too, as they do not account for periods of low wind and little sun, where sending a price signal to reduce electricity consumption in an all-renewables system may be even more important.

Our results clearly indicate that pricing can improve economic efficiency in residential electricity markets. But we also make a contribution in being the first to demonstrate the potential for electric vehicles to shift electricity load later into the night, effectively showing that an electric vehicle charging supply curve exists that may be used by utilities or other for-profit aggregators. Our finding of very little consumer response to the information treatments suggests that conservation appeals may be useful during times of crisis (Reiss and White 2008; Ito et al. 2018), and perhaps effective along with phone calls and social norms approaches (Brandon et al. 2018), but during normal summer days, such approaches alone are less likely to be effective.

The two programs of the experiment were performed in a heterogeneous neighborhood in a hot climate where many households were interested in solar energy and electric vehicles. We do not claim external validity to the entire United States. Indeed, it would be useful to perform a similar field experiment in other parts of the country. We believe that our results shed light on the effects one might expect for similar neighborhoods to the Mueller neighborhood, while our findings suggest the value of future work to extend or replicate our findings in other settings. As electric vehicle penetration increases, our results on the substantial potential for electric vehicle charging load shifting using a night low-pricing scheme will become increasingly relevant for greater parts of the country. From a policy perspective, it is useful to know where we are heading in the near future.

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. However, our results provide evidence of a household response to pricing that is relevant for understanding utility-run programs. Importantly, the results indicate that utilities could reduce carbon emissions and improve economic efficiency through pricing approaches to manage electricity load, and that this is likely to be ever more important with a high market share of intermittent renewables. In this study, our results lead us to focusing on air conditioning usage and electric vehicle charging, but as smart homes become more widespread with greater automation of appliances, additional opportunities for emission reductions and economic efficiency improvements will arise. Thus, while work remains to be done, examining the role of electricity conservation and load-shifting during peak and off-peak periods from the business and climate change standpoints seems well worth the effort required to provide deeper insights.

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Tables & Figures

Table 1: Use By Major Category (Percent)

Variable	Non-Summer	Summer	Event Period
Panel A: Use by major category			
adjustable	39.3	57.9	72.8
unadjustable	8.2	5.2	4.3
unmeasured	52.4	36.8	22.9
Panel B: Use by major appliance			
heating/cooling	15.9	45.2	63.2
washer/dryer	2.9	1.6	1.0
kitchen	9.3	5.3	4.5
Electric vehicle	4.8	3.0	1.9

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%.

Table 2: Balance of Observables

	Control		Treatment			
	mean	std. dev.	mean	std. dev.	mean diff	p-value
Non-event-day 4-7 PM Electric Use (kWh/minute)	2.42	0.008	2.37	0.008	0.05	0.72
Pre-Treatment Electric Use (kWh/minute)	0.84	0.001	0.99	0.001	-0.15	0.053
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 Temp (°F)	70.4	3.75	69.4	3.0	1.0	0.14
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)[1]	0.14	0	0.51	0	-0.37	0.00
1(Has programmable thermostat)	0.64	0.09	0.75	0.05	-0.11	0.27
Number of Residents	2.44	1.01	2.53	1.34	-0.09	0.71
Square Footage of House	1888	611	2070	701	-181	0.93

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. [1]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 pre-treatment period is defined as March-May 2013.

Table 3: Summer Event Treatment Effects

β^{TDPj} 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***
	(0.08)	(0.10)	(0.10)	(0.002)	(0.08)
Text + Action	-0.04	-0.04	-0.10	-0.001	-0.08
	(0.08)	(0.08)	(0.08)	(0.001)	(0.07)
Text Message	0.02	0.02	-0.07	-0.001	0.009
	(0.08)	(0.08)	(0.08)	(0.001)	(0.06)
Portal	0.05	0.04	-0.003	0.005	-0.02
	(0.08)	(0.08)	(0.098)	(0.003)	(0.08)
Household FE	N	Y	Y	Y	Y
Quarter of Sample FE	N	Y	Y	Y	Y
R-squared	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 non-adjustable 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. *** denotes p<0.01.

Table 4: Nighttime Off-Peak Pricing Experimental Program

	(1) Use *Original Sample*	(2) EV *Original Sample*	(3) Heating *Original Sample*	(4) EV *Expanded Control*	(5) EV *Matched Sample*
1(Treated × 10PM-2AM)	0.02	-0.08	0.03	-0.07	-0.09
	(0.07)	(0.07)	(0.05)	(0.06)	(0.09)
1(Treated × 2AM-6AM)	0.13*	0.11*	0.04	0.11**	0.17**
	(0.07)	(0.06)	(0.06)	(0.05)	(0.09)
Household FE	Y	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y	Y
R-squared	0.15	0.09	0.10	0.07	0.02
N	30m	13m	26m	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 hour. Regressions only include off-peak period hours (10PM-6AM) to exclude load shifting effects during non-treatment 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. * denotes p<0.01.

Table 5: Emissions

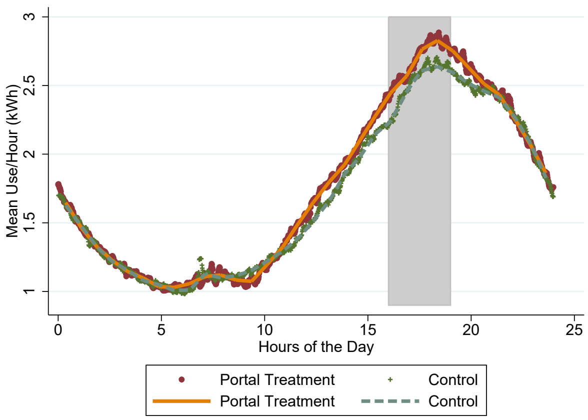
	CO_2	**SO_2**	**NO_x**
Panel A: Critical Peak Pricing Emissions			
Total Use Emissions Reductions (tons (lbs)/Texas/event)	-7,027.02	-7,541.82	-10,720.71
Social Cost of Total Use Emissions Reductions ($/Texas/event)	-351,351	-346,923	-10,720
AC Emissions Reductions (tons (lbs)/Texas/event)	-5,225.22	-5,608.02	-7,971.81
Social Cost of AC Emissions Reductions ($/Texas/event)	-261,261	-257,969	-55,803
Panel B: Additional Cooling Emissions			
Emissions from 1 °F (tons (lbs)/Texas/evening)	630.63	676.83	962.11
Social Cost from 1 °F ($/Texas/evening)	31,532	31,134	6,735
Emissions from 3 °F (tons (lbs)/Texas/evening)	1,891.89	2,030.49	2,886.34
Social Cost of 3 °F ($/Texas/evening)	94,595	93,403	20,204
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)	2,646	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, while 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 3-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 $50 ton. We use a $92,000 per ton cost of SO_2, and a $14,000 per ton cost of NO_x.

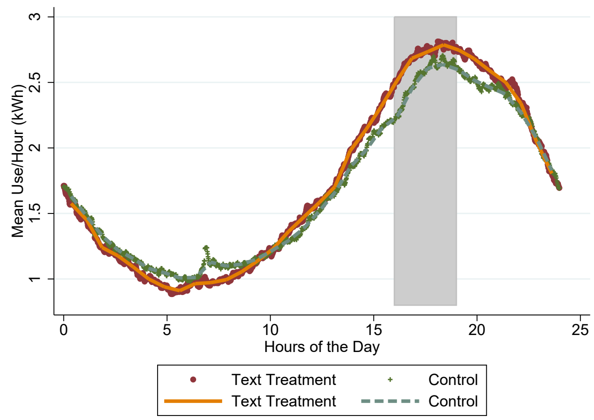
Table 6: Generation Costs

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 ($/Texas/evening)	58,550
Generation Costs from 3 °F ($/Texas/evening)	175,651
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

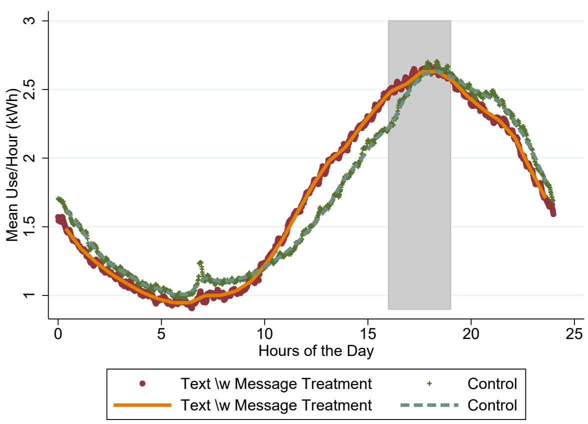
Notes: Panel A displays generation cost reductions from the CPP treatment effect for a single event period. Results are extrapolated to 11,000,000 houses in Texas. Panel B displays the additional generation cost from a 1 or 3 °F increase in temperatures above the preferred thermostat setting. The numbers are for 11,000,000 houses in Texas for a single 3-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.



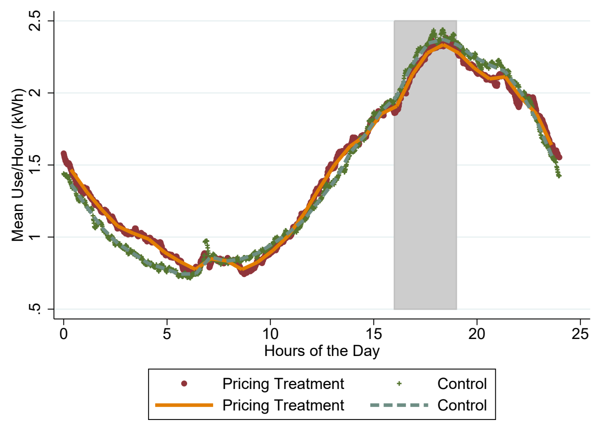
(a) Portal Treatment



(b) Simple Text Message Treatment

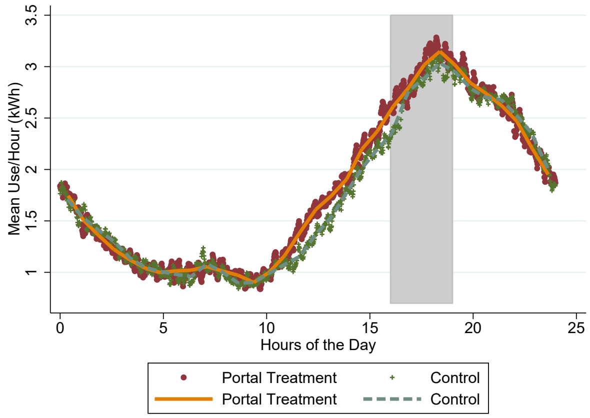


(c) Text w/ Message Treatment

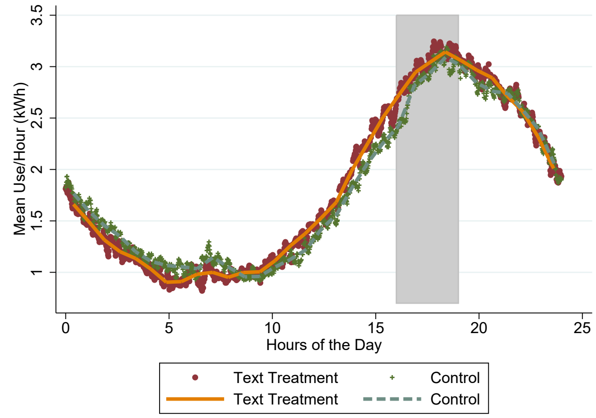


(d) Pricing Treatment

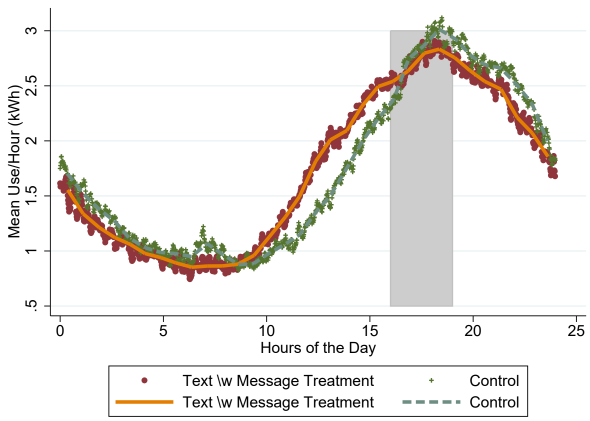
Figure 1: The plots display non-event day mean minute level use by treatment group net of a household fixed effect.



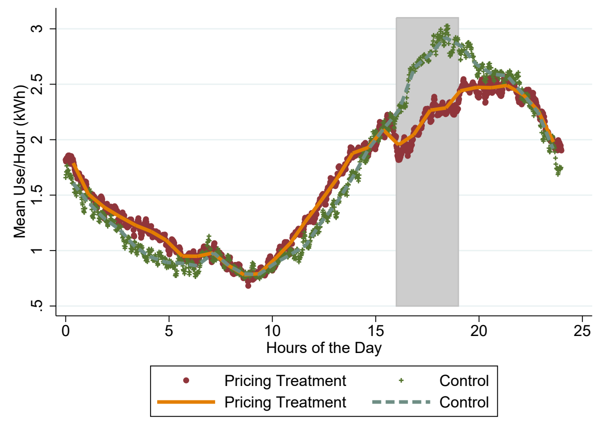
(a) Portal Treatment



(b) Simple Text Message Treatment



(c) Text w/ Message Treatment



(d) Pricing Treatment

Figure 2: The plots display event day mean minute level use by treatment group net of a household fixed effect.

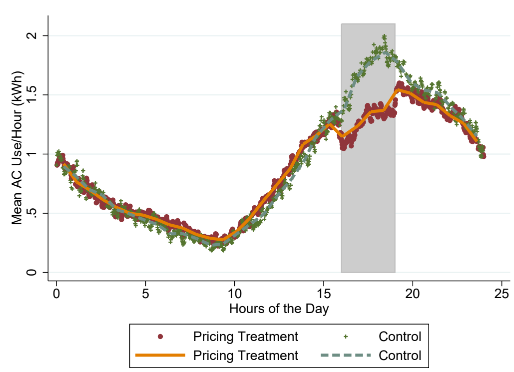
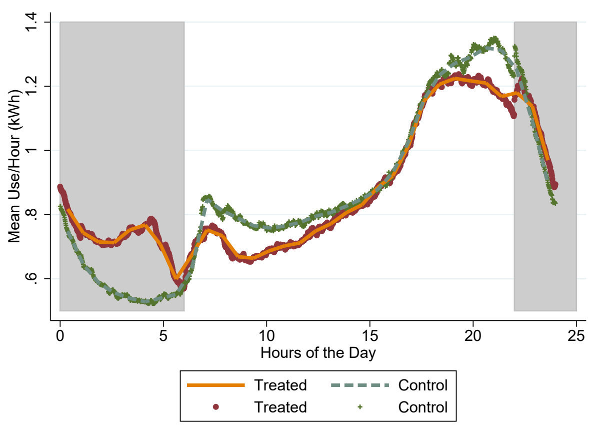
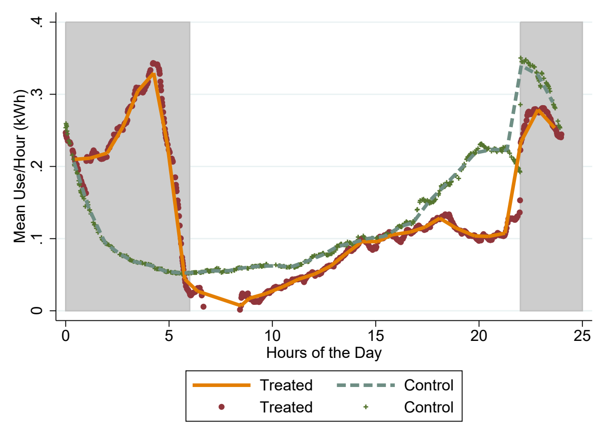


Figure 3: The plot displays event day mean minute level air conditioning (AC) use for the pricing treatment and control groups net of a household fixed effect.

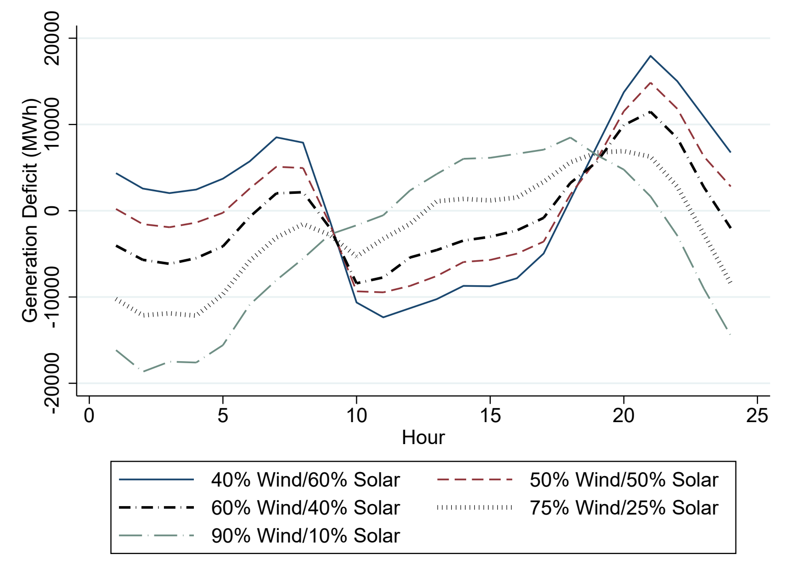


(a) Total Use



(b) Electric Vehicle Use

Figure 4: The plots display 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.



Generation Deficit (MWh)
-20000
-10000
0
10000
20000
0
5
10
15
20
25
Hour
40% Wind/60% Solar
50% Wind/50% Solar
60% Wind/40% Solar
75% Wind/25% Solar
90% Wind/10% Solar

Figure 5

ONLINE APPENDIX

A Further Details of the Field Experiment

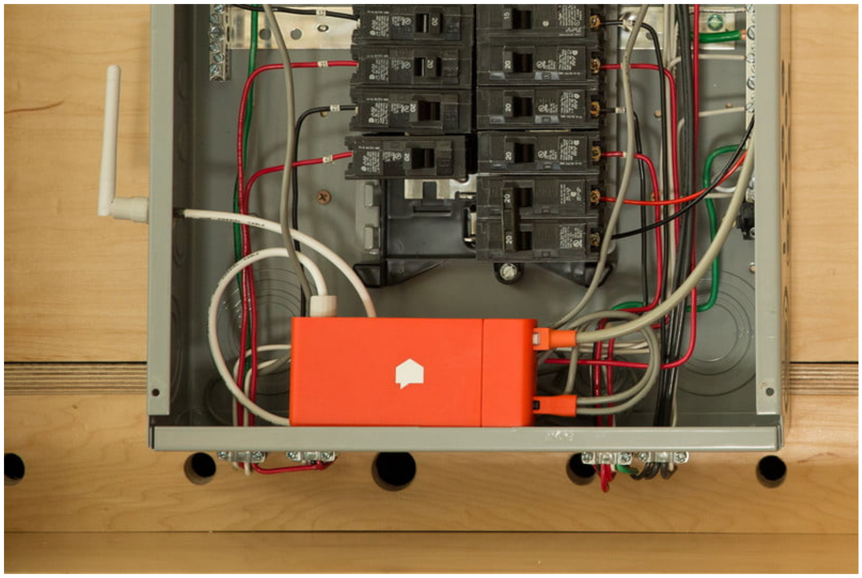
This short appendix provides further details of the field experiment. We begin with the language for the pricing treatment recruitment invitation:

Sign up now to take part in Pecan Street's electricity pricing trial! Pecan Street is conducting an experiment among its residential volunteers to determine whether, and to what extent, consumers are willing to alter electricity use by time of day. As a member of Pecan Street's research in Mueller, your participation is particularly valuable to this study and can enable you to earn up to $700.

Unlike most pricing trials, you will not be billed at a different rate by Austin Energy for participating. You will see your electricity bill unchanged by this study and will continue to be billed according to Austin Energy's existing rate structure. Instead, you will receive 1. a base credit of at least $150 and 2. monthly credits based on your household's response to an experimental electric rate that decreases late in the day to encourage nighttime electricity use and increases on predetermined days in the summer months.

Follow the pricing schedule and save based on these experimental rates? A monthly credit will be added to your base credit to be paid in full at the conclusion of the study, which can total up to $700. Opt not to follow the schedule and use electricity as usual? You will not be penalized and will owe no additional money to Austin Energy.

Next we provide an example of what a circuit-level meter looks like:



We also present a map of the Mueller neighborhood:

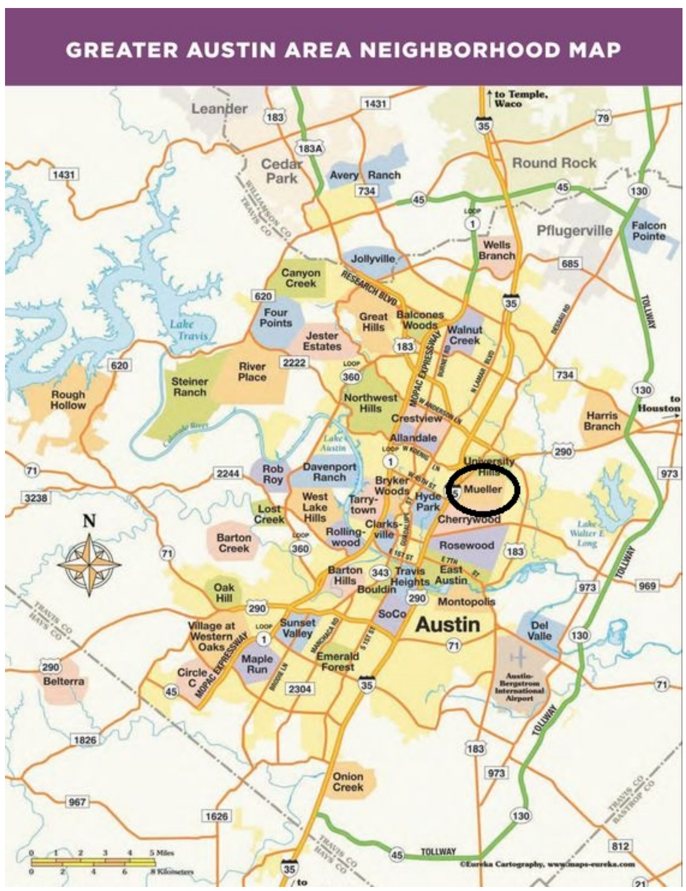


Figure A.1: Map of Austin and the Mueller Neighborhood

We now describe how the critical peak pricing (CPP) events were called. The CPP events are primarily driven by weather forecasts as high summer temperatures are highly correlated with high electricity demand. The utility had a limit of 15 events they could call per summer. Ideally, if the utility knew the daily maximum temperatures for every each day of the summer at the beginning of the summer, they could assign the 15 hottest days of the summer to be the CPP event days for that summer. Since it is not possible to know the temperature profile of an entire summer before it happens, the utility developed an algorithm to determine when a CPP event should be called, based on near-term temperature forecasts, how many events had been called so far each month, and how many days are left in each month. The company that was contracted to develop the pricing experiment and to determine when the CPP events occurred is called Frontier Associates LLC. The algorithm used to call the CPP events is laid out in the following flow chart created by the consultants running the experiment in their industry report Zarnikau et al. (2015).

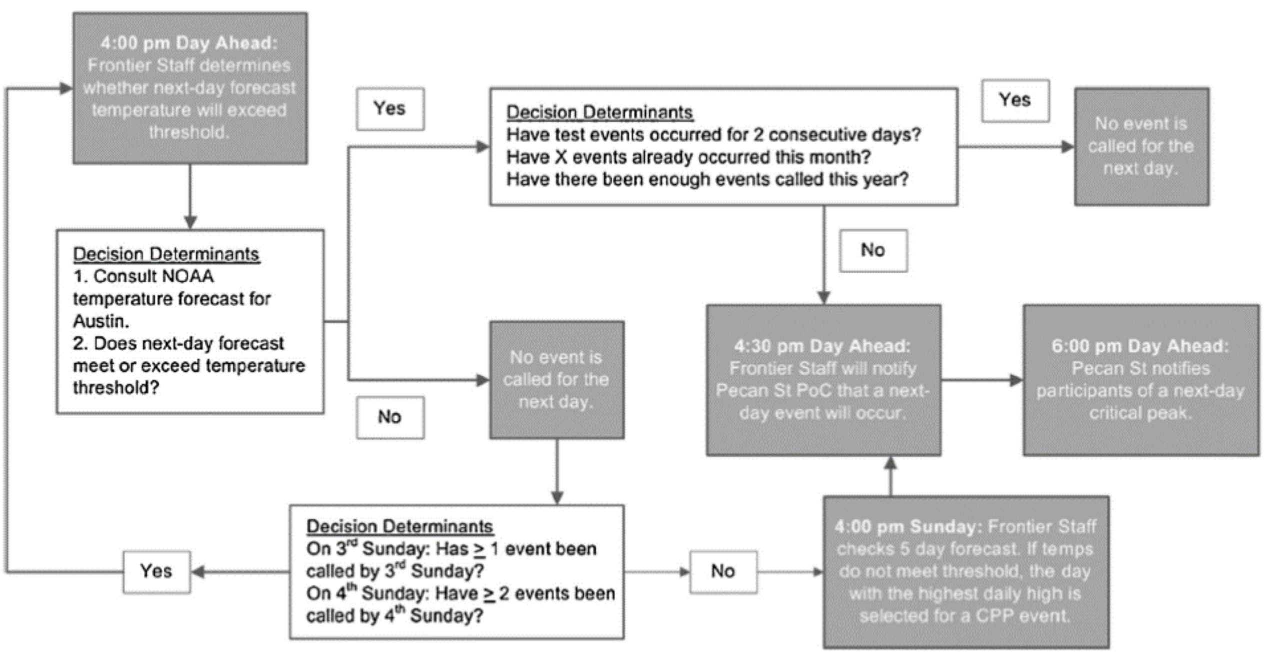


Figure A.2: Flow Chart Describing How CPP Events Are Called.

Finally, in Table A.1, we provide a comparison of demographic characteristics for the Mueller neighborhood with the broader city of Austin. It is not possible to formally test for differences using the aggregate Census data so in the final column of the table, we indicate whether the reported margins of error overlap. The margins of error overlap for income, unemployment rates, the fraction of the population with a high school diploma or more, the fraction of residents over 18, and the number of rooms per household. The margins of error do not overlap for the fraction of residents with more than a bachelors degree or the median home value.

Table A.1: Mueller Neighborhood and Broader Austin

	Austin		**Mueller Neighborhood**		**Margins of**
	Estimate	Margin of Error	Estimate	Margin of Error	**Error Overlap**
Median Household Income	\$55,216	±\$908	\$62,175	±\$7,742	Yes
Unemployment Rate	5%	±0.2%	3.2%	±2.4%	Yes
% High School Graduate or Higher	87%	±0.4%	91.4%	±6.7%	Yes
% Bachelor's Degree or Higher	46%	±0.5%	64.9%	±8.1%	No
% Residents over 65	7.3%	±0.1%	4.8%	±0.8%	No
% Residents over 18	21.8%	±0.2%	19.5%	±5.1%	Yes
Median Value Owner-Occupied Housing Units	\$227,800	±\$1,975	\$379,200	±\$33,782	No
Median Rooms Per House	4.7	±0.1	4.1	±0.7	Yes

Notes: Data source is the U.S. Census 2014 American Community Survey.

A.1 Austin Energy Standard Electricity Charges

Austin Energy was on a tiered rate schedule in 2013 and 2014. Households were charged a fixed per kWh rate plus a per kWh rate that increased with usage (an increasing block pricing system). Furthermore, all households were charged a flat \$10 fee for being connected to the service. The rates were as follows:

Total fixed per kWh charges:

- 4.654 cents/kWh in 2013
- 5.168 cents/kWh in 2014

The summer and winter tiers did not change between 2013 and 2014. The \$10 flat fee also did not change. For reference, the summer and winter tiers are presented in Table A.2.

Table A.2: Austin Energy Pricing Tiers (cents/kWh)

Tier	Winter	Summer
Tier 1: 0-500 kWh	1.8	3.3
Tier 2: 501-1000 kWh	5.6	8
Tier 3: 1001-1500 kWh	7.2	9.1
Tier 4: 1501-2500 kWh	8.4	11
Tier 5: $>$ 2500 kWh	9.6	11.4

The average monthly use for pricing treatment households in 2013 and 2014 during treatment months was 1034.897 kWh in 2013 and 1139.964 kWh in 2014. Thus, the average total electricity bill was $117.8397 per month or $0.1138 per kWh in 2013 and $138.1501 per month or $0.1212 per kWh in 2014. For reference, the critical peak experimental price was $0.64/kWh and the off-peak period experimental price was $0.0265/kWh.

B Further Data Description

B.1 Data Cleaning Procedure

In this subsection we outline the data cleaning process. We downloaded the raw minute level electricity consumption data from the Pecan Street Dataport website.[36] Academics can apply for free access to the data. In our regressions, we drop observations in which use by any appliance is larger than 10 kWh per minute or use is negative. This drops 0.29% of the total observations.

For some observations, appliance-specific consumption is missing in the raw data. We do not set these values to zero. Instead, we leave them as missing. This is why, for example, the number of observations in the air conditioning regressions reported in Table 3 is less than the number of observations in the total electricity use regressions.

[36] Website can be found here: https://dataport.cloud/

B.2 Additional Tables of Balance

This subsection of the appendix provides more detailed tables of balance comparing each of the individual treatments to the control group. Just as in Table 2, they provide evidence of successful randomization.

Table A.3: Balance of Observables for Pricing Treatment

	Control		Treatment		
	mean	std. dev.	mean	std. dev.	mean diff
Non-event-day 4-7 PM Electric Use (kWh/minute)	2.49	0.001	2.43	0.002	0.05
Pre-Treatment Electric Use (kWh/minute)	0.84	0.001	0.92	0.001	-0.078
Income (categorical)	4.61	1.27	4.41	1.32	0.19
Education (categorical)	1.58	0.57	1.73	0.45	-0.15
Preferred Thermostat Temp (°F)	70.38	3.75	69.52	2.99	0.86
Number of Televisions	1.72	1.06	1.43	0.73	0.28
1(Solar PV System)	0.08	0.27	0.27	0.45	-0.19*
Number of Residents	2.44	1.01	2.54	1.53	-0.10
Square Footage of House	1888	611	2017	615	-128
Has Programmable Thermostat	0.64	0.09	0.82	0.07	-0.18
1(Has Electric Vehicle)	0.14	0	0.51	0	-0.37

Notes: There are 30 houses in the pricing group that responded to most of the questions on the survey. The remainder are control houses. 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 = 80; N educ = 83; N temp = 83; N number of televisions = 82; N solar pv = 83; N residents = 76; N house square footage = 53; N Programmable Thermostat = 53. The pre-treatment period is defined as March-May 2013. If present, statistical differences would be denoted by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.4: Balance of Observables for Portal Treatment

	Control		Treatment		
	mean	std. dev.	mean	std. dev.	mean diff
Non-event-day 4-7 PM Electric Use (kWh/minute)	2.49	0.001	2.77	0.001	-0.28
Pre-Treatment Electric Use (kWh/minute)	0.84	0.001	0.97	0.001	-0.123
Income (categorical)	4.61	1.27	4.43	1.81	0.18
Education (categorical)	1.58	0.57	1.57	0.53	0.01
Preferred Thermostat Temp (°F)	70.38	3.75	69.57	2.57	0.81
Number of Televisions	1.72	1.06	2.00	1.15	-0.28
1(Solar PV System)	0.08	0.27	0.00	0	0.08
Number of Residents	2.44	1.01	2.67	1.37	-0.23
Square Footage of House	1888	611	2254	912	-365
Has Programmable Thermostat	0.64	0.09	0.72	0.14	-0.08
1(Has Electric Vehicle)	0.14	0	0.09	0	0.05

Notes: There are 7 houses in the portal group that responded to most of the questions on the survey. The remainder are control houses. 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 = 58; N educ = 60; N temp = 60; N number of televisions = 60; N solar pv = 60; N residents = 56; N house square footage = 36; N Programmable Thermostat = 36. The pre-treatment period is defined as March-May 2013. If present, statistical differences would be denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Balance of Observables for Text Treatment

	Control		Treatment		
	mean	std. dev.	mean	std. dev.	mean diff
Non-event-day 4-7 PM Electric Use (kWh/minute)	2.49	0.001	3.1	0.002	-0.61*
Pre-Treatment Electric Use (kWh/minute)	0.84	0.001	1.12	0.001	-0.278**
Income (categorical)	4.61	1.27	4.13	1.55	0.48
Education (categorical)	1.58	0.57	1.63	0.74	-0.04
Preferred Thermostat Temp (°F)	70.38	3.75	69.38	3.29	1.00
Number of Televisions	1.72	1.06	2.50	1.07	-0.78*
1(Solar PV System)	0.08	0.27	0.00	0.00	0.08
Number of Residents	2.44	1.01	2.13	1.64	0.32
Square Footage of House	1888	611	2177	799	-288
Has Programmable Thermostat	0.64	0.09	0.64	0.15	0.003
1(Has Electric Vehicle)	0.14	0	0.13	0	0.01

Notes: There are 8 houses in the text group that responded to most of the questions on the survey. The remainder are control houses. 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 = 59; N educ =61. N temp = 61; N number of televisions = 61; N solar pv = 61; N residents = 58; N house square footage = 37; N Programmable Thermostat = 36. The pre-treatment period is defined as March-May 2013. If present, statistical differences would be denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Balance of Observables for Text with Message

	Control		Treatment		
	mean	std. dev.	mean	std. dev.	mean diff
Non-event-day 4-7 PM Electric Use (kWh/minute)	2.49	0.001	2.87	0.001	-0.38
Pre-Treatment Electric Use (kWh/minute)	0.84	0.001	0.98	0.001	-0.139
Income (categorical)	4.61	1.27	3.83	1.27	0.78*
Education (categorical)	1.58	0.57	1.42	0.79	0.17
Preferred Thermostat Temp (°F)	70.38	3.75	69.08	3.48	1.29
Number of Televisions	1.72	1.06	1.83	0.84	-0.12
1(Solar PV System)	0.08	0.27	0.17	0.39	-0.09
Number of Residents	2.44	1.01	2.78	1.30	-0.34
Square Footage of House	1888	611	1919	632	-30
Has Programmable Thermostat	0.64	0.09	0.75	0.13	-0.11
1(Has Electric Vehicle)	0.14	0	0.14	0	-0.01

Notes: There are 9 houses in the text group that responded to most of the questions on the survey. The remainder are control houses. 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 = 63; N educ = 65; N temp = 65; N number of televisions = 65; N solar pv = 65; N residents = 59; N house square footage = 37; N Programmable Thermostat = 37. If present, statistical differences would be denoted by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B.3 Additional Summary Statistics

This subsection of the appendix provides additional summary statistics.

Table A.7: Average Total Electricity Usage by Treatment Group (kWh)

	mean	std. dev.	min	max	N
Panel A: Summer					
Pricing	1.63	1.73	0	10.0	19,456,889
Portal	2.02	1.91	0	10.0	14,023,059
Text Message	1.84	1.72	0	10.0	13,038,821
Text+Action	1.86	1.85	0	10.0	14,606,830
Control	1.62	1.77	0	10.0	17,253,418
Panel B: Non-Summer					
Pricing	0.95	1.33	0	10.0	28,852,697
Portal	1.11	1.27	0	10.0	21,207,853
Text Message	1.02	1.24	0	10.0	18,730,037
Text+Action	1.03	1.24	0	10.0	21,539,833
Control	0.84	1.14	0	10.0	25,132,252
Panel C: Critical Peak Pricing Event Period					
Pricing	2.41	2.05	0	10.0	270,802
Portal	3.39	2.11	0	10.0	194,079
Text Message	3.10	1.85	0	10.0	180,309
Text+Action	3.14	2.10	0	10.0	200,125
Control	2.79	2.01	0	10.0	240,186
Panel D: Nighttime Off-Peak Period					
Pricing	0.86	1.16	0	10.0	6,349,544
Portal	0.86	1.04	0	10.0	4,735,425
Text Message	0.80	0.99	0	10.0	4,217,009
Text+Action	0.82	1.04	0	10.0	4,876,809
Control	0.66	0.95	0	10.0	5,573,616

Notes: Summary statistics for electricity use (in units of kWh/hour) over the entire time frame of the experiment. An observation is a household-minute. We dropped values above 10 kWh per hour and below 0 kWh per hour (0.29% of the total number of observations).

Table A.8 provides the average temperature per month per year on critical peak treatment days.

Table A.8: Maximum Temperatures on Treatment Days in Celsius

	2013	2014	Both
June	38.02	34.18	36.48
	(3)	(2)	(5)
July	35.26	36.55	36.12
	(2)	(4)	(6)
August	37.01	35.74	36.38
	(5)	(5)	(10)
September	34.67	32.31	33.10
	(2)	(4)	(6)

Notes: This table presents the average daily maximum temperature on treatment days by month. Column 1 is for 2013 only, column 2 is for 2014 only, and column 3 is both years pooled. The number of treatment days in each month is reported in parentheses below the temperatures.

C Further Nighttime Off-Peak Treatment Figures

In this section we present additional off-peak period graphs. The first, Figure A.3 displays the off-peak pricing period figure, similar to Figure 4a, but for houses without an electric vehicle. The second, Figure A.4 presents the off-peak pricing experimental period figure for heating electricity use only.

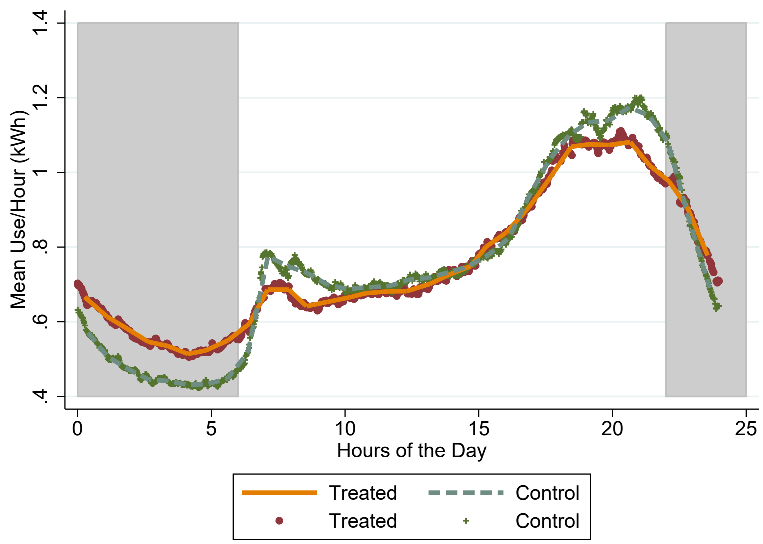


Figure A.3: Off-peak pricing treatment use for houses w/out electric vehicles net of a household fixed effect.

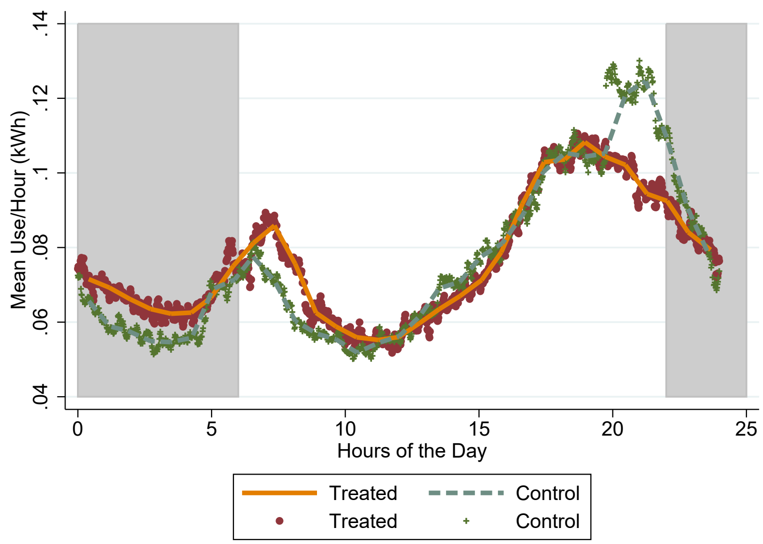


Figure A.4: Off-peak pricing treatment heating use net of a household fixed effect.

D Robustness Checks and External Validity

D.1 Robustness Checks

In this appendix subsection, we present several additional robustness checks.

First, we examine our results in a diff-in-diff specification where we exploit only two sources of variation: the differences across the treatment and control and the differences across event minutes and non-event minutes. Recall that the preferred specification also uses variation from differences across event days and non-event days. If one was worried that event days are systematically different than non-event days, one would not want to rely on this variation. Thus, we estimate a specification similar to Equation (1) using data only from event days. Specifically, we estimate,

$$Y_{it} = \sum_j \beta^j T_{ijt} + \mathbf{X}\boldsymbol{\gamma} + \rho_i + \boldsymbol{\phi}(t) + \varepsilon_{it}, \tag{3}$$

where Y_{it} is the electricity usage 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). This variable takes the value of zero for all control houses. The interaction terms other than the difference-in-differences terms are absorbed by the following fixed effects. ρ_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. Column 1 of Table A.9 displays the results of estimating our primary model restricted to the sample of event days. The estimated coefficient of -0.42 is very slightly larger than our preferred specification in Table 3, but is quite similar and is again statistically significant.

Second, Table A.14 and Table A.17 provide evidence that houses in the pricing treatment group continue to use less energy than control houses one hour (7PM-8PM) after the CPP treatment period end. Our triple-difference specification uses this time period as a control period. Thus, if there are spillovers to this non-experimental period, then our coefficients may be biased. To account for this we drop the hours 7PM-8PM (and 8PM-9PM to be safe) in our triple-differences specification. Column 2 of Table A.9 displays the results. To be clear, we estimate Equation 1 but drop the hours 7PM-9PM. Importantly, the treatment effect estimates in this specification are nearly identical to our primary estimates, so this omission is not pivotal to our results at all.

Third, we estimate our primary model after taking the natural log of the dependent variable. The results are reported in Column 3 of Table A.9. The estimated coefficient indicates that the pricing treatment reduces electricity consumption by approximately 31% during the peak hours. Specifically, we estimate Equation 1, but the dependent variable (use) is logged.

Fourth, we examine the robustness of our results to using a different control group. Recall that Pecan Street, Inc also collected minute-level usage data for an additional 24 households in Austin outside of the Mueller neighborhood. These houses were not informed of the critical peak pricing study and were not receiving any other treatment at this time, and thus serve as a useful second control group as well as providing insight into the external validity of our results. We estimate our primary model (Equation 1) replacing the original control group with these additional 24 houses. The results are presented in Column 4 of Table A.9. Again, the treatment effect is somewhat smaller, but broadly consistent with the primary treatment effect reported in Table 3. We prefer our larger control group to this alternative control group.

Next, we estimate the summer peak pricing treatment effects (Equation 1) replacing the dependent variable with electric vehicle electricity usage, all unaccounted usage, clotheswasher usage, dryer usage, bathroom electricity usage, and livingroom electricity usage. Recall that unaccounted use is defined as the total use minus the use from all measured appliances (including air conditioners and electric vehicles). Table A.10 presents the results. We find that the critical peak pricing experiment did not appear to impact electric vehicle or unaccounted electricity use.

Table A.9: Robustness: Primary Treatment Effects

	(1) Electricity Use DiD	(2) Electricity Use	(3) Log(Elect Use)	(4) Alternative Control
Portal	0.20	0.04	-0.06	0.13
	(0.14)	(0.08)	(0.05)	(0.09)
Text Message	0.10	0.02	-0.03	0.11
	(0.12)	(0.08)	(0.05)	(0.09)
Text + Action	0.09	-0.04	-0.08*	0.05
	(0.13)	(0.08)	(0.04)	(0.09)
Pricing	-0.42***	-0.39***	-0.31***	-0.31***
	(0.15)	(0.09)	(0.06)	(0.11)
Household FE	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y
R-squared	0.16	0.16	0.30	0.17
N	8.7m	194m	191m	159m

Notes: Column 1 displays diff-in-diff estimates of estimating (1) only on the sample restricted to event days. Column 2 is our primary treatment effects specification dropping observations that occurred 1-2 hours after the critical peak program. Column 3 displays the primary specification with logged overall use as the outcome variable. Column 4 uses an alternative control group consisting of houses in the greater Austin area. Only triple-difference coefficients shown; all other interactions are included in the regressions. An observation is a household-minute and electricity use is in units of kWh per hour. The average control group usage during the event periods is 2.79 kWh per minute. Standard errors clustered on i in parentheses. * denotes $p<0.1$.

We now move on to examine our results using 15-minute level data, rather than minute-level data. One might argue that the variation at the minute level is too fine and too prone to measurement error and thus aggregating to the 15-minute level is preferred. The coefficients are roughly identical to the coefficients in Table 3 only divided by 15. For example, the coefficient on total electricity use in column (1) is -6.06 and $-6.06/15 = -0.40$, which is almost exactly our coefficient using the minute level data. To be clear, we estimate Equation 1 but use 15-minute level data instead of minute-level data.

D.2 External Validity

External validity is a key question about our study. Recall that Table A.1 above compares census block data from the Mueller neighborhood to Austin more broadly. While one can never fully claim external validity without running an experiment in multiple places, we perform a test to explore whether these discrepancies matter based on observables. Specifically, we limit the sample to houses with similar incomes and education levels to the Texas average. The average income in Texas is $57,051 according to the US Census. The Pecan Street household surveys report categorical income categories. We select all houses in the $50,000-$74,999 income category. 89.7% of the Texas population has less than a graduate degree. We further limit our sample to households with a Bachelors degree or less. We then re-estimate our primary results table (Table 3) using this subsample of data. The results for the pricing treatment are presented in Table A.12. Importantly, the results are generally consistent with the main findings.

D.3 Pre-cooling Suggestive Results

This subsection presents a table of the suggestive results for pre-cooling. Specifically, we estimate an equation similar to Equation 1 with AC use as the dependent variable, but change the treatment period to be the two hours prior to the treatment period (2PM-4PM) on event days in Column 1 and the hour prior to the treatment period on non-event days in Column 2. We also drop the hours 4PM-7PM, the actual treatment period, from the analysis. In all other respects, the model is the same as Equation 1.

We show the results for the text+action group as this is the group that received the message to pre-cool the home. The treatment coefficient in Column (1) is statistically significant at the 10% level and suggests a 0.15 kWh per hour increase in air conditioning consumption during the pre-cooling hours for the households that received the pre-cooling text message. Column (2) presents the coefficient for the treated households during the non-event days, which is not statistically significant. However, the coefficient is positive, at 0.07, so we view this result as only suggestive.

Table A.10: Effect of Summer Peak Pricing on Further Appliances

	Electric Vehicle	Unaccounted	Washer	Dryer	Bathroom	Livingroom
Portal	-0.007	0.01	-0.06	-0.01	0.04	0.05
	(0.03)	(0.05)	(0.04)	(0.01)	(0.05)	(0.14)
Text Message	-0.03	0.001	0.03	0.003	0.07	0.22
	(0.03)	(0.05)	(0.04)	(0.01)	(0.11)	(0.15)
Text + Action	-0.02	-0.05	-0.04	-0.01	0.003	0.07
	(0.03)	(0.04)	(0.04)	(0.01)	(0.03)	(0.19)
Pricing	-0.008	-0.06	-0.03	-0.01	0.01	0.09
	(0.03)	(0.04)	(0.03)	(0.01)	(0.02)	(0.12)
Household FE	Y	Y	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y	Y	Y
R-squared	0.03	0.32	0.27	0.23	0.35	0.55
N	80m	78m	82m	97m	37m	36m

Notes: This table replicates the primary treatment effect specification, Equation 1, but with electric vehicles usage, unaccounted usage, clotheswasher usage, dryer usage, bathroom electricity usage, and livingroom electricity usage as the dependent variables. Unaccounted usage is total consumption minus consumption by all measured appliances. An observation is a household-minute and electricity use is in units of kWh per hour. Standard errors clustered on i in parentheses. The average control group total electricity usage during the event periods is 2.79 kWh per minute. Summary statistics on the other appliances can be found in Table 1.

Table A.11: Robust: Summer Event Treatment Effects with 15 Minute Level Data

β^{TDPj} coefficients	(1) Electricity Use	(2) AC only	(3) adjustable (include AC)	(4) nonadjustable
Portal	0.43	-0.63	-0.49	0.07
	(1.27)	(1.07)	(1.32)	(0.05)
Text Message	0.04	-0.03	-0.85	-0.01
	(1.23)	(0.95)	(1.15)	(0.02)
Text + Action	-0.80	-0.95	-1.14	-0.008
	(1.18)	(0.96)	(1.17)	(0.02)
Pricing	-6.06***	-3.06***	-4.15***	-0.009
	(1.48)	(1.06)	(1.30)	(0.003)
Household FE	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y
R-squared	0.22	0.14	0.20	0.26
N	12,938,955	12,976,531	12,976,427	12,976,132

Notes: Triple-difference coefficients shown; all other interactions in (1) are included. An observation is a household-15 minute interval and electricity use is in units of kWh per hour. Standard errors clustered on i in parentheses. The number of observations changes in each column because not all households have each category individually-metered. The average control group usage during the event periods is 41.85 kWh per 15 minute interval. ** denotes $p<0.05$.

Table A.12: Summer Event Treatment Effects on Census Sample

β^{TDPj} coefficients	(1) Electricity Use	(2) AC only	(3) adjustable (include AC)	(4) nonadjustable
Pricing	-0.44***	-0.37***	-0.41**	-0.002
	(0.14)	(0.10)	(0.15)	(0.001)
Household FE	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y
R-squared	0.11	0.04	0.12	0.31
N	12m	11m	11m	11m

Notes: This table replicates the primary results table limiting to households with similar income and education characteristics as Texas as a whole. The median household income in Texas is $57,051 according to the US Census. The Pecan Street household surveys have categorical income brackets. We select all houses in the $50,000-$74,999 income category and below. Also, 89.7% of the Texas population has less than a graduate degree. We limit to households with Bachelors degrees or less. The number of houses included in each sub-treatment group is as follows: control = 6, portal = 1, text = 1, text with action message = 2, pricing = 5. Because of the extremely low sample size for the 3 information treatments, we only show the pricing treatment results. 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 hour. Standard errors clustered on i in parentheses. The number of observations changes in each column because not all households have each category individually-metered. The average control group usage during the event periods is 2.79 kWh per minute. *** denotes p<0.01, ** p<0.05.

Table A.13: Treatment Effect on Pre-Cool Days from 2-4 PM

β^{TDPj} coefficients	(1) AC Use (kWh) Pre-Cool Message	(2) AC Use (kWh) non-Event-Days
Text + Action	0.15*	0.07
	(0.08)	(0.04)
Household FE	Y	Y
Quarter of Sample FE	Y	Y
R-squared	0.06	0.06
N	126m	137m

Notes: Only triple-difference coefficients shown; all other pricing ones in (1) are included. An observation is a household-minute and electricity use is in units of kWh per hour. Standard errors clustered on i in parentheses. The average control group usage during the event periods is 2.79 kWh per minute. * denotes p<0.1.

D.4 Are People Home? Adjustable Use on Summer Event Days

An important question is whether or not residents were home and thus able to respond to price changes during the critical peak event periods. If people simply left their house during the event hours and used electricity elsewhere, then the residential electricity reductions may be offset by increases elsewhere. In the Pecan Street survey, one of the questions asks if people worked from home. 62% of surveyed houses have at least one person that works from home, which could include stay-at-home parents. This suggests that many people should be home during the event periods, but it is still possible that people leave because of the events.

To further provide evidence that residents are at home during the event periods, we graph the average adjustable appliance use per treatment group on critical peak event days and similarly hot summer days. Adjustable appliances include lights, bathroom use, bedroom use, clothes washer use, dining room use, dishwasher use, dryer use, kitchen and kitchen appliance use, living room use, and office use. If people actually leave their homes during the high price event periods in order to reduce electricity use and save money, we would expect to see a difference in the use of all of these appliances. Figure A.5 shows the adjustable use on event days and similarly hot ($> 90°$) non-event days. The gray shaded area is the experimental pricing period. The two lines are pretty much on top of each other, ruling out that people leave their homes during the event periods.

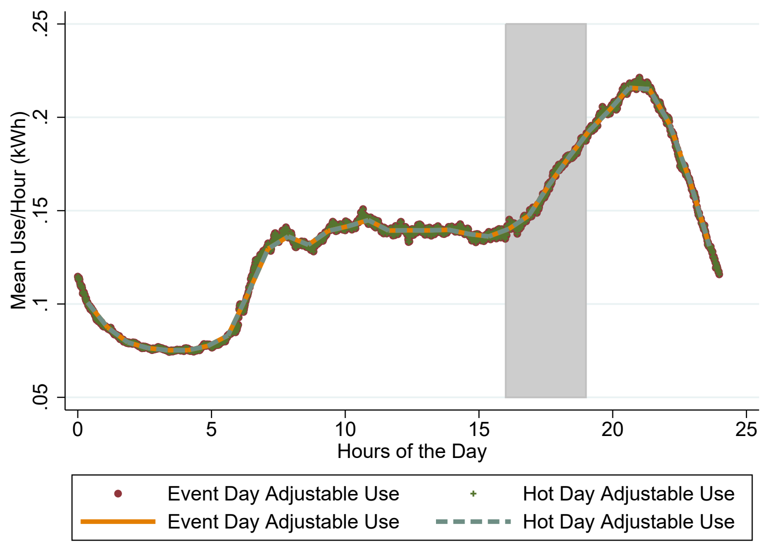


Figure A.5: This figure displays the mean adjustable use on event days and similarly hot non-event days for pricing treatment and control groups net of a household fixed effect.

D.5 Pricing Experiment Estimates By Hour and Month

This subsection further evaluates both pricing experiments by looking at treatment effects over particular hours of the day. We examine the nighttime off-peak pricing experiment by hour of the night, providing additional information beyond Table 4. We see similar results, but with greater statistical significance during a few key morning hours. We also present CPP pricing treatment effects by hour of the day in Table A.16 and for specific 30-minute intervals in Table A.15.

First, we augment Equation 2 with additional time period interactions. Specifically, we estimate the following equation:

$$Y_{it} = \sum_h \beta^h T_{iht} + \rho_i + \boldsymbol{\phi}(t) + u_{it}, \tag{4}$$

where Y_{it} is again electricity usage by household i in minute t, T_{iht} is a dummy for being a treated household in the nighttime pricing treatment group during the hour of the night h, where h is each hour over the night from 10PM-6AM. As before, ρ_i are household fixed effects, and $\boldsymbol{\phi}(t)$ are fixed effects for each 15-minute interval in the sample. In column 5 we employ a matching routine by which we match treated houses with EVs to control houses with EVs based on pre-treatment electric vehicle use. We use Stata's psmatch2 program to perform a 1-1 nearest neighbor matching routine. When then estimate our primary nighttime experiment regression, Equation 2, and Equation 4, with weights provided by the psmatch2 program.

Second, we estimate an equation similar to Equation 1, but only for the pricing treatment and control groups and with additional time period interaction terms as follows:

$$Y_{it} = \sum_h \beta^h \mathbf{H}_h CPP_i E_t + \mathbf{X}\boldsymbol{\gamma} + \rho_i + \boldsymbol{\phi}(t) + \varepsilon_{it}, \tag{5}$$

where Y_{it} is the electricity usage by household i in minute of the sample t. CPP_i is a dummy variable indicating that household i is in the pricing treatment group. $\mathbf{H}_h$ is a series of dummy variables indicating the time periods 3PM-3:30PM, 3:30PM-4PM, 4PM-

Table A.14: Off-Peak Pricing Results By Hour

	(1) Use *Original Sample*	(2) EV *Original Sample*	(3) Heating *Original Sample*	(4) EV *Expanded Control*	(5) EV *Matched Sample*
1(Treated × 10PM-11PM)	-0.06	-0.16	0.01	-0.15	-0.08
	(0.10)	(0.13)	(0.04)	(0.11)	(0.14)
1(Treated × 11PM-12AM)	0.03	-0.11	0.03	-0.09	-0.27
	(0.09)	(0.11)	(0.05)	(0.09)	(0.20)
1(Treated × 12AM-1AM)	0.03	-0.06	0.04	-0.05	-0.11
	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)
1(Treated × 1AM-2AM)	0.08	0.03	0.05	0.00	0.07
	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)
1(Treated × 2AM-3AM)	0.12	0.09	0.04	0.09	0.23**
	(0.07)	(0.07)	(0.06)	(0.06)	(0.10)
1(Treated × 3AM-4AM)	0.18**	0.16*	0.04	0.16**	0.27**
	(0.08)	(0.09)	(0.06)	(0.07)	(0.11)
1(Treated × 4AM-5AM)	0.19**	0.18*	0.04	0.16**	0.20*
	(0.09)	(0.10)	(0.06)	(0.07)	(0.10)
1(Treated × 5AM-6AM)	0.05	0.02	0.05	0.02	-0.04
	(0.08)	(0.07)	(0.07)	(0.05)	(0.05)
Household FE	Y	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y	Y
R-squared	0.14	0.10	0.09	0.07	0.02
N	30m	13m	26m	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. Only triple-difference coefficients shown; all other interactions in Equation (2) are included. 'Use' refers to total electricity consumption; 'EV' refers to electric vehicle electricity consumption. An observation is a household-minute and electricity use is in units of kWh per hour. Regressions only include off-peak period hours (10PM-6AM) to exclude load shifting effects during non-treatment hours as evidenced by Figure 4a. 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. Standard errors clustered on i in parentheses. The average control group usage during the nighttime experiment hours is 0.66 kWh per minute. ** denotes p<0.05. * denotes p<0.01.

7PM, 7PM-7:30PM, and 7:30PM-8PM with time periods indexed by h. E_t is a indicator equal to 1 if the day is a CPP event day and zero otherwise. This is identical to our triple difference specification in Equation 1, however, in Equation 1, $\mathbf{H}_h$ is replaced with a simple indicator for the event period: 4PM-7PM. In Equation 1, the interactions of CPP_i, E_t, and the dummy for the event period, 4PM-7PM, in this case defined as $\mathbf{H}_h$, results in our triple differences variable, T_{ijt}. All other interaction terms other than the difference-in-differences terms are either contained in $\mathbf{X}$ or absorbed by the following fixed effects. ρ_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. The results are presented in Table A.15.

Table A.15: Critical Peak Pricing Spillovers

	(1) Total Use	(2) AC Use
1(Treated × 3:00-3:30PM Pre-Period)	-0.02	0.03
	(0.08)	(0.07)
1(Treated × 3:30-4:00PM Pre-Period)	-0.08	-0.03
	(0.08)	(0.07)
1(Treated × 4:00-7:00PM Treatment Period)	-0.40***	-0.30***
	(0.10)	(0.08)
1(Treated × 7:00-7:30PM Post-Period)	-0.23**	-0.18***
	(0.09)	(0.07)
1(Treated × 7:30-8:00PM Post-Period)	-0.16*	-0.14**
	(0.09)	(0.06)
Household FE	Y	Y
Quarter of Sample FE	Y	Y
R-squared	0.14	0.06
N	91m	74m

Notes: Dependent variable in (1) is total electricity use; in (2) is air conditioning (AC) use. Only spillover triple-difference coefficients shown; all other variables in (2) are included. An observation is a household-minute and electricity use is in units of kWh per hour. The number of observations declines from Table 3 because models in this table include the pricing treatment and control group only. Standard errors clustered on i in parentheses. The average control group usage during the event periods is 2.79 kWh per minute. *** denotes p<0.01, ** p<0.05, * p<0.1.

Third, we estimate an equation similar to Equation 1, but again only for the pricing treatment and control groups and with additional interaction terms as follows:

$$Y_{it} = \sum_h \beta^h \mathbf{H}_h CPP_i E_t + \mathbf{X}\boldsymbol{\gamma} + \rho_i + \boldsymbol{\phi}(t) + \varepsilon_{it}, \tag{6}$$

where Y_{it} is the electricity usage by household i in minute of the sample t. CPP_i is a dummy variable indicating that household i is in the pricing treatment group. In this equation, $\mathbf{H}_h$ is a series of dummy variables indicating each hour of the day with hours indexed by h. E_t is a indicator equal to 1 if the day is a CPP event day and zero otherwise. This is identical to our triple difference specification in Equation 1, however, in Equation 1, $\mathbf{H}_h$ is replaced with a simple indicator for the event period: 4PM-7PM. All other interaction terms other than the difference-in-differences terms are either contained in $\mathbf{X}$ or absorbed by the following fixed effects. ρ_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. The results are presented in Table A.16.

Table A.16: Pricing Treatment Effect By Hour of Treatment Day

	(1) Use	(2) AC
1(Treated × 12PM-1AM)	-0.04	-0.03
	(0.08)	(0.07)
1(Treated × 1AM-2AM)	-0.09	-0.07
	(0.07)	(0.06)
1(Treated × 2AM-3AM)	-0.05	-0.04
	(0.06)	(0.05)
1(Treated × 3AM-4AM)	-0.03	-0.03
	(0.06)	(0.05)
1(Treated × 4AM-5AM)	-0.03	-0.02
	(0.05)	(0.04)
1(Treated × 5AM-6AM)	-0.02	-0.02
	(0.05)	(0.04)
1(Treated × 6AM-7AM)	-0.07	-0.01
	(0.05)	(0.03)
1(Treated × 7AM-8AM)	-0.06	-0.00
	(0.06)	(0.03)
1(Treated × 8AM-9AM)	-0.04	-0.03
	(0.05)	(0.04)
1(Treated × 9AM-10AM)	-0.04	-0.01
	(0.06)	(0.04)
1(Treated × 10AM-11AM)	-0.05	-0.01
	(0.07)	(0.05)
1(Treated × 11AM-12AM)	0.03	0.03
	(0.07)	(0.06)
1(Treated × 12AM-1PM)	0.08	0.04
	(0.08)	(0.07)
1(Treated × 1PM-2PM)	0.10	0.06
	(0.10)	(0.08)
1(Treated × 2PM-3PM)	0.01	0.02
	(0.10)	(0.09)
1(Treated × 3PM-4PM)	-0.07	-0.02
	(0.10)	(0.09)
1(Treated × 4PM-5PM)	-0.37***	-0.25**
	(0.12)	(0.10)
1(Treated × 5PM-6PM)	-0.44***	-0.35***
	(0.12)	(0.10)
1(Treated × 6PM-7PM)	-0.47***	-0.36***
	(0.12)	(0.10)
1(Treated × 7PM-8PM)	-0.21**	-0.18**
	(0.10)	(0.09)
1(Treated × 8PM-9PM)	-0.08	-0.09
	(0.10)	(0.08)
1(Treated × 9PM-10PM)	0.01	-0.06
	(0.10)	(0.08)
1(Treated × 10PM-11PM)	-0.02	-0.03
	(0.09)	(0.08)
1(Treated × 11PM-12PM)	-0.05	-0.06
	(0.10)	(0.08)
Household FE	Y	Y
Quarter of Sample FE	Y	Y
R-squared	0.14	0.06
N	91m	74m

Notes: Dependent variable in (1) is total electricity use; in (2) is air conditioning (AC) use. Only triple-difference coefficients shown; all other interactions are included. An observation is a household-minute and electricity use is in units of kWh per hour. Standard errors clustered on i in parentheses. The average control group usage during the event periods is 2.79 kWh per minute. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

D.6 Critical Peak Pricing Estimates By Month of Sample

Next we estimate treatment effects by month of the sample. To do so we estimate,

$$Y_{it} = \sum_{m} \beta^{m} \mathbf{M}_{m} CPP_{i} E_{t} Z_{t} + \mathbf{X}\boldsymbol{\gamma} + \rho_{i} + \boldsymbol{\phi}(t) + \varepsilon_{it}, \tag{7}$$

where Y_{it} is the electricity usage by household i in minute of the sample t. CPP_i is a dummy variable indicating that household i is in the pricing treatment group. Z_t is an indicator for the event period 4PM-7PM. E_t is a indicator equal to 1 if the day is a CPP event day and zero otherwise. The interaction of CPP_i, Z_t, and E_t creates the triple difference variable in in Equation 1, T_{ijt}. However, in this alternative specification, we interact the triple difference variable with indicators for each month of the treatment period denoted $\mathbf{M}_m$. This is a set of dummy variables for each treatment period month from June-Sept 2013 and June-Sept 2014. All other interaction terms other than the difference-in-differences terms are either contained in $\mathbf{X}$ or absorbed by the following fixed effects. ρ_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. The results are presented in Table A.17.

Table A.17: Pricing Treatment Effect By Month

	(1) Use	(2) AC
1(Treated × June) 2013	-0.84***	-0.65***
	(0.15)	(0.13)
1(Treated × July) 2013	-0.33**	-0.18*
	(0.15)	(0.11)
1(Treated × Aug) 2013	-0.34**	-0.17*
	(0.14)	(0.10)
1(Treated × Sept) 2013	-0.46***	-0.27**
	(0.14)	(0.11)
1(Treated × June) 2014	-0.12	-0.14*
	(0.11)	(0.07)
1(Treated × July) 2014	-0.09	-0.16**
	(0.11)	(0.06)
1(Treated × Aug) 2014	-0.11	-0.15*
	(0.12)	(0.08)
1(Treated × Sept) 2014	-0.20**	-0.17**
	(0.10)	(0.07)
Household FE	Y	Y
Quarter of Sample FE	Y	Y
R-squared	0.14	0.06
N	91m	74m

Notes: Dependent variable in (1) is total electricity use; in (2) is air conditioning (AC) use. Only triple-difference coefficients shown; all other interactions are included. An observation is a household-minute and electricity use is in units of kWh per hour. Standard errors clustered on i in parentheses. The average control group usage during the event periods is 2.79 kWh per minute. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

E Heterogeneous Treatment Effects

In each of the following tables, we estimate our primary specification, Equation 1, but interact the triple differences coefficients, T_{ijt}, with each of the demographic variables listed in the tables or with usage tiers. The dependent variable is always total use but the number of observations in each specification changes because we do not have information on all of the demographics for each of the houses.

Table A.18: Heterogeneous Treatment Effects 1

	(1)	(2)	(3)	(4)
	Use	Use	Use	Use
Pricing	-0.21	-3.82***	-0.46***	-0.54***
	(0.30)	(0.10)	(0.13)	(0.08)
Text + Action	-0.02	-1.86	-0.01	0.26
	(0.31)	(1.62)	(0.15)	(0.21)
Text Message	0.06	-1.44	-0.12	0.13
	(0.36)	(2.17)	(0.14)	(0.20)
Portal	0.17	-0.45	0.13	0.19
	(0.41)	(2.23)	(0.19)	(0.30)
Pricing*house sqft	-0.0002			
	(0.0002)			
Text + Action*house sqft	0.0001			
	(0.0002)			
Text Message*house sqft	0.0000			
	(0.0001)			
Portal*house sqft	0.0001			
	(0.0002)			
Pricing*Preferred Temp		0.04**		
		(0.02)		
Text + Action*Preferred Temp		0.02		
		(0.02)		
Text Message*Preferred Temp		0.02		
		(0.03)		
Portal*Preferred Temp		0.01		
		(0.03)		
Pricing*1(PV)			-0.14	
			(0.15)	
Text + Action*1(PV)			0.16	
			(0.16)	
Text Message*1(PV)			0.35**	
			(0.17)	
Portal*1(PV)			0.46*	
			(0.25)	
Pricing*1(Program Thermo)				-0.04
				(0.17)
Text + Action*1(Program Thermo)				-0.21
				(0.21)
Text Message*1(Program Thermo)				-0.14
				(0.22)
Portal*1(Program Thermo)				0.15
				(0.34)
House FE	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y
R-squared	0.17	0.17	0.17	0.17
N	63m	62m	64m	63m

Notes: Dependent variable in each regression is total use. Each demographic is interacted with all triple difference variable, but only the treatment effect interactions are shown. Preferred temp is preferred thermostat setting in the summer months. PV and Program Thermo are dummies for the existence of solar PV or programmable thermostats. The sample sizes are lower than the original sample because the demographics were collected from a survey of the control and treated houses with less than a 100% response rate. Standard errors clustered by household. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.19: Heterogeneous Treatment Effects 2

	(1) Use	(2) Use	(3) Use	(4) Use
Pricing	-0.18	-0.45	-0.91***	-0.71*
	(0.28)	(0.28)	(0.23)	(0.36)
Text + Action	-0.14	-0.01	-0.19	-0.07
	(0.17)	(0.37)	(0.17)	(0.28)
Text Message	3.58**	-0.04	-0.14	0.47
	(1.34)	(0.63)	(0.17)	(0.32)
Portal	-0.30	0.99	0.48	0.37
	(0.24)	(0.72)	(0.27)	(0.31)
Pricing*Education	-0.22			
	(0.19)			
Text + Action*Education	0.12			
	(0.10)			
Text Message*Education	-1.77**			
	(0.66)			
Portal*Education	0.30			
	(0.18)			
Pricing*Income		-0.02		
		(0.06)		
Text + Action*Income		0.02		
		(0.08)		
Text Message*Income		0.03		
		(0.13)		
Portal*Income		-0.10		
		(0.13)		
Pricing*# Residents			0.14*	
			(0.07)	
Text + Action*# Residents			0.11**	
			(0.05)	
Text Message*# Residents			0.08*	
			(0.04)	
Portal*# Residents			-0.06	
			(0.09)	
Pricing*TV Count				0.01
				(0.12)
Text + Action*TV Count				0.07
				(0.12)
Text Message*TV Count				-0.24**
				(0.10)
Portal*TV Count				-0.04
				(0.08)
House FE	Y	Y	Y	Y
Quarter of Sample FE	Y	Y	Y	Y
R-squared	0.17	0.17	0.17	0.18
N	63m	57m	64m	38m

Notes: Dependent variable in each regression is total use. Each demographic is interacted with all triple difference variable, but only the treatment effect interactions are shown. Income and education are measured as continuous categories. For example, income = 0 indicates an income range of $10,000-$19,999 while income = 2 indicates a range of $20,000-$34,999. Education = 0 indicates only high school, some college, trade, or vocational school. Education = 1 indicates college graduate. Education = 2 indicates postgraduate. The sample sizes are lower than the original sample because the demographics were collected from a survey of the control and treated houses with less than a 100% response rate. Standard errors clustered by household. *** denotes p<0.01, ** p<0.05, * p<0.1.

Table A.20: Treatment Effects by Use Tier

	(1)	(2)
	Use	Use
Pricing	-1.10***	-0.44**
	(0.28)	(0.28)
Pricing*Tier	0.21***	
	(0.17)	
Pricing*1(Tier 1)		-0.31
		(0.22)
Pricing*1(Tier 2)		-0.35
		(0.23)
Pricing*1(Tier 3)		0.03
		(0.20)
Pricing*1(Tier 4)		-0.11
		(0.25)
House FE	Y	Y
Quarter of Sample FE	Y	Y
R-squared	0.16	0.16
N	83m	83m

Notes: Dependent variable in each regression is total use. Tier is a continuous variable between 1 and 5 indicating which billing tier each household is in during each monthly billing cycle. Tier 1 through tier 4 are dummy variables indicating that a household is in a given pricing tier in a given month. The 5th tier is omitted due to collinearity. Standard errors clustered by household. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

F Emissions and Marginal Cost Calculations and Deep Decarbonization Simulation

F.1 Emissions and Marginal Cost of Generation Analyses

In this section we discuss how our experimental results impact electricity generation costs and emissions. To do so, we combine several publicly available datasets. Hourly load and net generation by fuel type (wind, solar, coal, natural gas, nuclear, etc.) are gathered from ERCOT for 2013-2020.[37][38] Net generation is reported every 15 minutes, which we aggregate to the hourly level. Hourly system lambda, an estimate of the hourly marginal costs for each ISO are downloaded from FERC form 714. Average hourly system lambda for the CPP event days, for the summer, and for the winter are reported in Table A.27.

We begin by replicating the marginal emissions calculations in Zivin et al. (2014) for ERCOT between 2013-2014. The equation is the following:

$$E_t^k = \beta_0 + \beta_1 Load_t + \beta_2(Load_t * 1(P)) + \beta_3 wind_t + \beta_4 solar_t + \omega_t + \epsilon_t, \tag{8}$$

where E_t^k is aggregate emissions of type k for k in CO_2, SO_2, and NO_x for ERCOT during hour t, $Load_t$ is the hourly load for ERCOT during hour t, $1(P)$ is an indicator for peak hours (4PM-7PM) during the summer months, the CPP event periods only (i.e., 4PM-7PM on CPP event days), or the nighttime treatment hours (10PM-6AM) during the nighttime treatment months. The terms $wind_t$ and $solar_t$ are controls for the amount of wind and solar generation in ERCOT during hour t and ω_t is an hour by month-of-sample fixed effect. Standard errors are clustered at the level of the fixed effects.

Tables A.21, A.22, and A.23 display the results of estimating Equation 8 for our event periods only, for all summer peak periods (4PM-7PM), and nighttime hours (10PM-6AM), respectively. The results indicate that marginal emissions across the three pollutants are generally lower during peak periods than other times of the day, but marginal CO_2 emis-

[37] http://www.ercot.com/gridinfo/load/load_hist/

[38] http://www.ercot.com/gridinfo/generation

sions increase during the nighttime. These results are unsurprising as the marginal fuel is natural gas during the peak periods whereas the base load fuel is often coal. Tables A.24 and A.25 display the marginal emissions calculations for 2019, for reference.

Next, we have preferred thermostat settings for a subset of houses, which we define as Preferred Temperature. We merge our electricity consumption data with actual temperature data (NOAA) and we construct a variable defined as $\Omega_i t$=max{Actual Temperature - Preferred Temperature,0}. For this calculation we use the maximum daily temperature in degrees F. We use this variable to estimate the electricity required to cool a home as outdoor temperatures increase by one degree above the preferred indoor temperature. The equation is

$$Y_{it} = \beta_0 + \beta_1 \Omega_{it} + \beta_2 sqft_i + \beta_3(\Omega_{it} * sqft_i) + +\epsilon_t, \tag{9}$$

where Y_{it} is total electricity use for house i during minute t and $sqft_i$ is the square footage of house i. Standard errors are clustered at the household level. We generated marginal effects for the average sized house in our dataset with results presented in Table A.26. The results in columns 3 and 4, which incorporate a house fixed effect, indicate that a one degree increase in the outdoor temperature above the preferred indoor thermostat setting increases electricity and AC use by 0.035 and 0.029 kWh for the average sized house during the peak hours in 2013-2014.

We combine all of this information to generate some useful calculations on the implications of our results. Table 5 displays our emissions calculations. Panel A displays the daily emissions reductions associated with the CPP treatment effect. We apply the treatment effect to the three CPP hours (4PM-7PM) and extrapolate the results to all residential households in Texas.[39] We find that if all houses in Texas received the CPP treatment, we would see an average reduction in CO_2, SO_2, and NO_x emissions of 7,027 tons, 7,542 lbs, and 10,720 lbs respectively. Using a \$50/ton social cost of carbon, 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 \$351,351, \$346,923, and \$75,044 per CPP event period for each pollutant respectively.

[39]We assume 11,000,000 houses in Texas throughout. See `https://www.census.gov/quickfacts/TX`

Panel A also displays the social benefits of the CPP air conditioning treatment. On average the AC benefits are approximately 75% of the total use benefits.

Panel B of Table 6 displays the additional emissions and social costs associated with 1 °F and 3 °F increases in maximum temperatures above preferred thermostat settings.[40] The social cost of additional emissions associated with a 1 °F increase above preferred temperatures is $31,532 for CO_2, $13,134 for SO_2, and $6,735 for NO_x for cooling all residences in Texas between 4PM-7PM. The social cost of additional emissions associated with a 3 °F increase above preferred temperatures is $94,595 for CO_2, $93,403 for SO_2, and $20,204 for NO_x for cooling all residences in Texas between 4PM-7PM. These results shed light on the social costs associated with cooling homes as temperatures increase due to climate change. These results also help provide context for the magnitude of the CPP treatment effects. The CPP estimates indicate that the reduction in emissions from reduced air conditioning due to the CPP treatment is more than double the emissions associated with an increase in outdoor temperature of three degrees. This highlights the substantial effect of the treatment.

Panel C of Table 6 displays the additional emissions and social costs associated with the increase in electricity use caused by the nighttime price reduction experiment. The first row displays the additional emissions associated with the nighttime treatment effect extrapolated to all registered EVs in Texas for one day.[41] The second row displays the emissions if these vehicles were charged during the day. To get this value, we take the nighttime treatment effect and multiply it by the marginal emissions during the non-nighttime hours (6AM-9PM). The third row displays the increase in emissions from the change in charging profile extrapolated to the entire treatment period (Nov-Dec and March-May). Finally, the last row of Panel C shows the social costs of these additional emissions, which are low ($13,405).

[40] NOAA predicts a 3 °F average temperature increase in Texas by 2050. https://www.climate.gov/news-features/featured-images/future-temperature-and-precipitation-change-colorado

[41] There are 52,190 EVs registered in Texas. https://electrek.co/2021/08/24/current-ev-registrations-in-the-us-how-does-your-state-stack-up/

Table 6 displays similar calculations for marginal generation costs. Panel of Table 6 uses the system lambda values in Table A.27 to determine the reduction in generation costs associated with the CPP treatment effect for 1 house per event period in row 1 and for all houses in Texas per event period in row 2. To do so, we multiply the marginal costs in \$/kWh by the CPP treatment effect multiplied by 3 hours. This produces a reduction in generation costs of \$0.059 per house per treatment period or \$652,419 if all houses in Texas received the treatment.

Panel B of Table 6 displays the additional generation costs associated with 1 °F and 3 °F temperature increases above preferred thermostat settings. A 1 °F increase in temperature above preferred thermostat settings increases generation costs by \$58,550 per evening (4PM-7PM) across all houses in Texas while a 3 °F increase in temperature above preferred thermostat settings increases generation costs by \$175,651 per evening across all houses in Texas.

Panel C of Table 6 displays the reduced generation costs associated with the nighttime treatment effect. The first row displays the generation costs of charging one EV between 1AM-5AM, the second row extrapolates this to all EVs in Texas across the entire treatment period, the third row displays the generation costs of charging one EV between 6AM-9PM, and the fourth row extrapolates this to all EVs in Texas across the entire treatment period. The final row in Panel C displays the reduction in generation costs from the nighttime treatment period (\$26,157 across all EVs for the entire treatment period).

Table A.21: Event Day Emissions 2013-14

	(1) CO2	(2) SO2	(3) NOx
Load (MWh)	0.585***	1.404***	0.781***
	(0.016)	(0.192)	(0.054)
Load (MWh)*1(Peak)	-0.039	-0.818***	0.052
	(0.030)	(0.305)	(0.118)
Month-by-hour FE	Y	Y	Y
R-squared	0.997	0.844	0.980
N	391	391	391

Notes: Dependent variable in each regression is total ERCOT emissions by hour of CO2 (masstons), SO2 (masslbs), and NOx (masslbs). Load is total ERCOT load in MWh by hour and peak is a dummy for the hours between 4PM and 7PM inclusive. The samples are limited to June-September 2013-2014 to align with the peak period pricing experiment timing. *** denotes p<0.01, ** p<0.05, * p<0.1.

Table A.22: Peak Period Emissions 2013-14

	(1) CO2	(2) SO2	(3) NOx
Load (MWh)	0.629***	1.267***	0.641***
	(0.003)	(0.044)	(0.013)
Load (MWh)*1(Peak)	-0.028***	-0.382***	0.074***
	(0.006)	(0.089)	(0.027)
Month-by-hour FE	Y	Y	Y
R-squared	0.991	0.778	0.824
N	9775	9775	9775

Notes: Dependent variable in each regression is total ERCOT emissions by hour of CO2 (masstons), SO2 (masslbs), and NOx (masslbs). Load is total ERCOT load in MWh by hour and peak is a dummy for the hours between 4PM and 7PM inclusive. The samples are limited to June-September 2013-2014 to align with the peak period pricing experiment timing. *** denotes p<0.01, ** p<0.05, * p<0.1.

Table A.23: Nighttime Emissions 2013-14

	(1) CO2	(2) SO2	(3) NOx
Load (MWh)	0.592***	0.882***	0.600***
	(0.005)	(0.040)	(0.012)
Load (MWh)*1(Nighttime)	0.013**	0.057	0.003
	(0.006)	(0.044)	(0.013)
Month-by-hour FE	Y	Y	Y
R-squared	0.986	0.872	0.886
N	18170	18170	18170

Notes: Dependent variable in each regression is total ERCOT emissions by hour of CO2 (masstons), SO2 (masslbs), and NOx (masslbs). Load is total ERCOT load in MWh by hour and nighttime is a dummy for the hours between 10PM and 5AM inclusive. The samples are limited to January-March and November and December 2013-2014 to align with the nighttime pricing experiment timing. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.24: Peak Period Emissions 2019

	(1) CO2	(2) SO2	(3) NOx
Load (MWh)	0.615***	0.606***	0.755***
	(0.006)	(0.053)	(0.045)
Load (MWh)*1(Peak)	-0.001	-0.135	0.370***
	(0.006)	(0.105)	(0.062)
Month-by-hour FE	Y	Y	Y
R-squared	0.996	0.851	0.947
N	2093	2093	2093

Notes: Dependent variable in each regression is total ERCOT emissions by hour of CO2 (masstons), SO2 (masslbs), and NOx (masslbs). Load is total ERCOT load in MWh by hour and peak is a dummy for the hours between 4PM and 7PM inclusive. The samples are limited to June-September 2013-2014 to align with the peak period pricing experiment timing. *** denotes $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.25: Nighttime Emissions 2019

	(1) CO2	(2) SO2	(3) NOx
Load (MWh)	0.600***	0.834***	0.603***
	(0.004)	(0.033)	(0.011)
Load (MWh)*1(Nighttime)	0.008	0.056	-0.022*
Month-by-hour FE	Y	Y	Y
R-squared	0.982	0.885	0.918
N	11891	11891	11891

Notes: Dependent variable in each regression is total ERCOT emissions by hour of CO2 (masstons), SO2 (masslbs), and NOx (masslbs). Load is total ERCOT load in MWh by hour and nighttime is a dummy for the hours between 10PM and 5AM inclusive. The samples are limited to January-March and November and December 2013-2014 to align with the nighttime pricing experiment timing. *** denotes p<0.01, ** p<0.05, * p<0.1.

Table A.26: Temperature Effects on Use

	(1) Use	(2) AC	(3) Use	(4) AC
Temp (F)-Preferred (F)	0.009	0.013	0.022*	0.018**
	(0.030)	(0.015)	(0.012)	(0.008)
House Sqft (1,000s)	0.486*	0.320*		
	(0.263)	(0.166)		
(Temp (F)-Preferred (F))*Sqft	0.020	0.012	0.007	0.006
	(0.015)	(0.007)	(0.007)	(0.005)
House FE			Y	Y
Effect for Average House	0.049***	0.035***	0.035***	0.029***
Standard Errors for Avg Effect	(0.008)	(0.004)	(0.003)	(0.002)
R-squared	0.094	0.087	0.301	0.245
N	1057547	873480	1057547	873480

Notes: Dependent variable in each regression is either total use or AC use. Temp (F) - Preferred (F) is the daily maximum temperature less the preferred thermostat setting. If this value is less than zero we set the variable to zero. House square feet is square feet in 1,000s. (Temp (F)-Preferred (F))*Sqft is the interaction between the two. The effect for the average house is estimated using the delta method. The average house is 1,946 square feet. *** denotes p<0.01, ** p<0.05, * p<0.1.

Table A.27: Average System Lambda ($/MWh)

Hour	Event Periods	Summer	Winter
0	25.34	24.87	23.34
1	24.15	24.01	22.5
2	23.68	23.17	21.96
3	23.45	23.21	22.3
4	24.35	23.67	24.32
5	26.15	24.61	24.55
6	26.45	25.68	26.92
7	28.08	26.97	32.96
8	29.43	28.77	30.46
9	33.08	31.7	31.26
10	37.24	34.78	32.22
11	41.22	38.79	31.11
12	47.34	42.11	30.01
13	50.79	45.76	29.57
14	53.75	50.13	28.97
15	51.39	48.32	28.23
16	46.94	44.38	27.78
17	42.18	39.99	29.05
18	38.66	36.55	34.02
19	37.44	34.78	33.74
20	34.59	32.53	32.16
21	31.12	30.21	29.79
22	29.39	28.55	28.26
23	27.43	26.38	25.49

Notes: This table reports the average system Lambda for CPP event periods only, for the summer (June through September), and for the winter treatment period (January-March and November and December). The average generation cost for the CPP event periods is $50.69/MWh. The average generation cost for the wind treatment period (nighttime during the winter) is $24.09/MWh. The average generation cost for the daytime during the winter is $30.52/MWh. Note these are simple averages and not calculated from a regression.

F.2 Simulation

For further analysis, we gather monthly generator-level coal and natural gas expenditures, total energy input in million Btus (MMBtu), and total electricity produced in MWh for 2013-2020. We use this data to construct each fossil fuel generator's heat rate (total energy input (MMBtu)/total electricity output (MWh)). We then multiply the heat rate by fuel expenditures to get an estimate of each generator's variable cost in $/MWh, which we combine with nameplate capacity data from EIA form 860 to construct simulated monthly supply curves for ERCOT. This construction assumes perfect competition. We drop variable cost values above the 99th percentile and below the 1st percentile of all variable costs as some are unrealistically high (e.g., $5,000/MWh) and some are unrealistically low (e.e.g, $0.43/MWh). The mean variable cost in the data is $38.32/MWh with a minimum of $15.21/MWh and a maximum of $239.07/MWh. As an example of the simulated supply curves, we show the March 2013 supply curve in Figure A.6. Finally, we again use the generator level hourly emissions from the Environmental Protection Agency's Continuous Emissions Monitoring System (CEMS).[42]

Next, we want to think about decarbonizing the Texas grid. To do so, we imagine that we shut down all coal and natural gas production. Figure A.7 displays the difference between the actual hourly fossil fuel generation and wind and solar generation on average in 2020. Another way to think of this is the additional renewables needed to supply ERCOT on average if fossil fuels shut down. Figure A.8 displays the average wind and solar utilization rates per hour in 2020, which will be used in the simulation. These are calculated by dividing the total wind and solar generation for each hour in 2020 by the wind and solar capacity in ERCOT.

We can begin to tell a decarbonization story using these pieces of information. We first assume that we can scale up wind and solar capacity to be equal to the fossil fuel (coal and natural gas) capacity in 2020. We then explore different mixes of wind and solar capacity to determine which mix minimizes the production deficit if fossil fuel generation

[42] `https://www.eia.gov/electricity/data/emissions/`

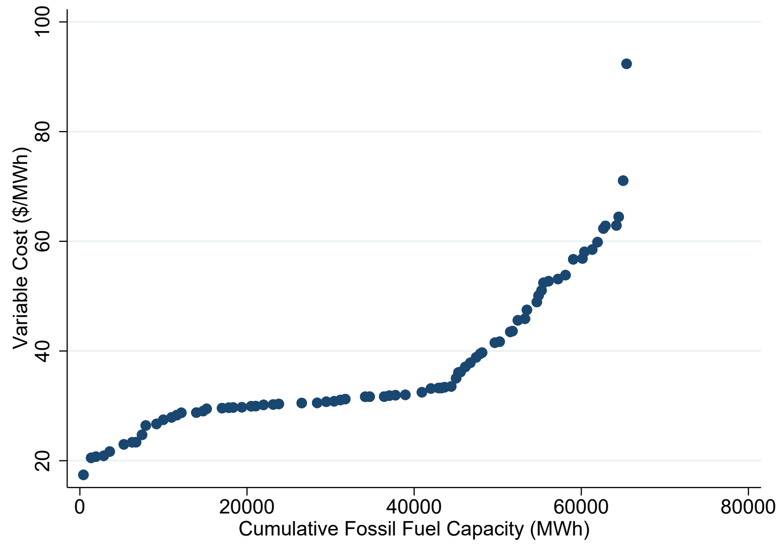


Figure A.6: The plot displays variable costs by fossil fuel generator in ERCOT in March 2013.

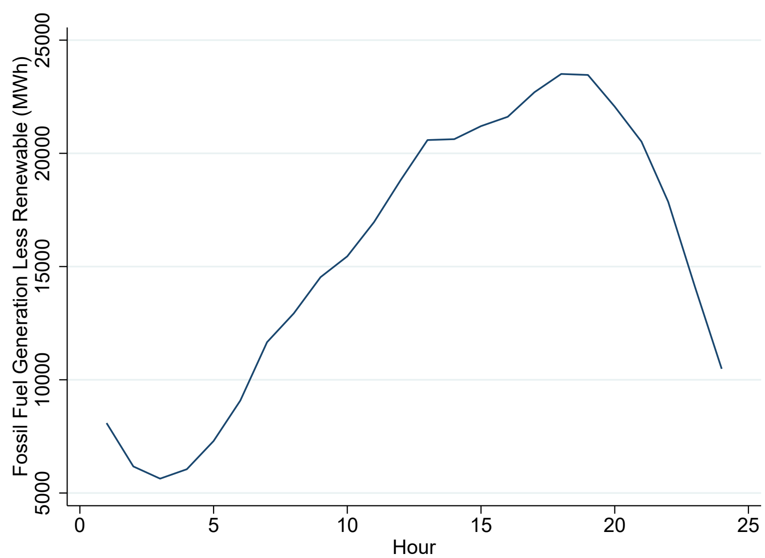


Figure A.7

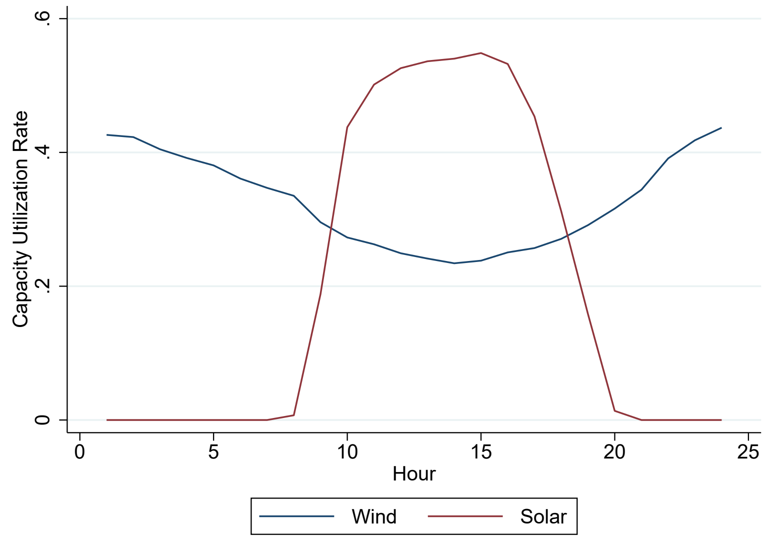


Figure A.8

is replaced by renewables. To do so, we scale up renewable capacity, divide it up into fractions of wind and solar, multiply by the actual wind and solar hourly utilization rates (e.g., A.8), and subtract the result from hourly fossil fuel generation. The end product provides the generation surplus or deficit for each hour in 2020 under our alternative grid. The results for different renewable mixes are displayed in Figure A.9. The results indicate that some hours experience surplus generation and some hours (the peak) experience shortages up to nearly 20,000 MWh. The surplus and shortages depend on the mix of wind and solar. In general, higher fractions of wind power appear to minimize generation deficits

If we assume we have battery storage, we can collapse the hourly surpluses and deficits to generate estimates of the total surplus or deficit over each day. For instance, the surplus in Figure A.9 would be stored and used when there is a deficit. The results for each wind/solar generation mix are presented in row 1 of Table A.28. Next, we can ask how much the CPP treatment effect would reduce the shortages. Surpluses are negative and deficits are positive. Therefore, a negative value is good for the grid. To do so, we multiply the total load for each hour by the average fraction of electricity demand

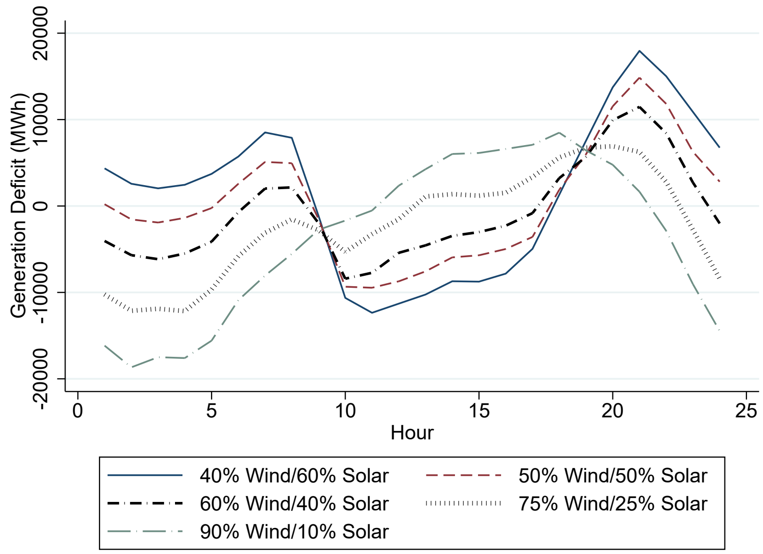


Figure A.9

that is residential (43%) and by the CPP treatment effect in percentage terms and subtract this from the total load. This results in a slightly smaller demand for each hour. This analysis assumes that the CPP is a constant percentage across all hours and across all households. The results are presented in row 2 of Table A.28. While this may be unrealistic, it gives a sense of the magnitude of reduction we might expect from applying the CPP more broadly. The 90% wind generation mix minimizes the generation deficit with and without the CPP.

Table A.28: Daily Generation Surpluses and Deficits (MWh)

	40% Wind	50% Wind	60% Wind	75% Wind	90% Wind
Surplus/Deficit	53431	21644	-10143	-57824	-105505
Surplus/Deficit Under CPP	8315	-23471	-55259	-102940	-150621

Notes: This table presents the daily sum of the generation presented in Figure A.9. Surpluses are negative and deficits are positive. Therefore, a negative value is good for the grid.

We can then determine how much battery storage capacity would be required to meet each of the renewable mix scenarios in MW/day. To do so, we take the average of the hourly deficits (e.g., Figure A.9) for all hours 2020 and then find the maximum over all hours. This can be considered a maximum of the mean. This provides an estimate of the average daily load that is not immediately met by the additional counterfactual renewable generation (i.e., the need for battery storage in MWh). The results are presented in Table A.29. We also find the maximum need for battery storage over all hours in 2020 by taking the maximum of the hourly deficits for all hours in 2020. The results are presented in Table A.30.

Table A.29: Average Daily Need for Battery Storage (MW)

	40% Wind	50% Wind	60% Wind	75% Wind	90% Wind
Maximum Average Hourly Deficit	16,144	12,746	9,349	5,449	4,437
Maximum Average Deficit Under CPP	13,975	10,577	7,180	3,185	2,089
Savings from CPP	2,169	2,169	2,169	2,264	2,348

Notes: This table takes the average of the hourly deficits and surpluses in Figure A.9 for 2020 and then takes the maximum over all hours. Therefore, these numbers represent the average battery storage capacity required to meet the generation deficit on the average day. The battery would have to be used for more than one hour, but this is the capacity required to meet the hourly deficit.

Table A.30: Maximum Daily Need for Battery Storage (MW)

	40% Wind	50% Wind	60% Wind	75% Wind	90% Wind
Max Hourly Deficit	46369	46403	46453	46428	46453
Max Deficit Under CPP	42828	42862	42912	42887	42912
Savings from CPP	3541	3541	3541	3541	3541

Notes: This table takes the maximum of the hourly deficits and surpluses in Figure A.9 for 2020 and then takes the maximum over all hours. Therefore, these numbers represent the maximum battery storage capacity required to meet the generation deficit on the maximum day. The battery would have to be used for more than one hour, but this is the capacity required to meet the hourly deficit.

Our analysis indicates that the 90% wind/10% solar mix under the CPP minimizes the need for battery storage on average. The CPP reduces the need for batteries by about 2,348 MW on average, assuming there is a CPP reduction in every hour of the day and energy can only be stored and used within a 24 hour period. ERCOT would only need around 2,000 MW of battery storage with coal and natural gas capacity replaced by wind and solar capacity on average. However, the average does not tell the entire story. To avoid blackouts, the grid would need storage capacity to meet the highest demand net of renewable generation, which is equivalent to the maximum deficit. To meet this load, ERCOT would need approximately 43GW of battery storage.

Finally, how much would the CPP save in generation costs if ERCOT maintained several natural gas generators? Using the supply curve generated above, we get the fol-

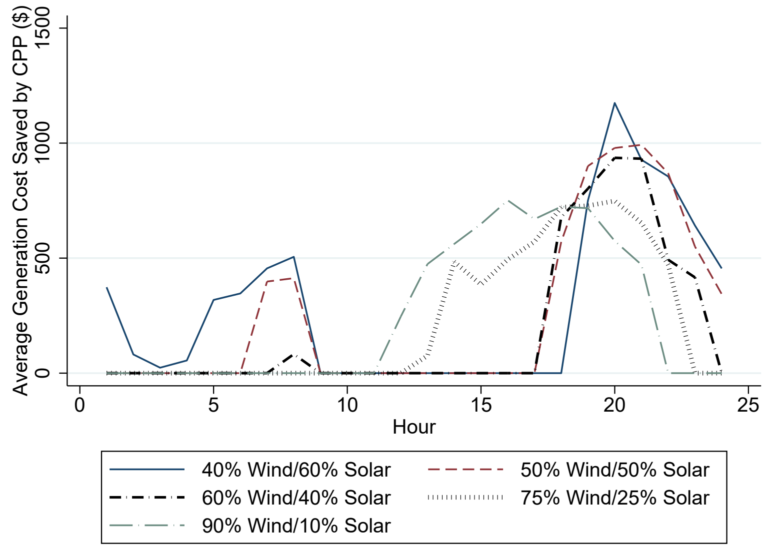


Figure A.10

lowing graphs for the different wind/solar mix scenarios. The first presents the average generation cost saved while the second presents the maximum cost saved over 2020.

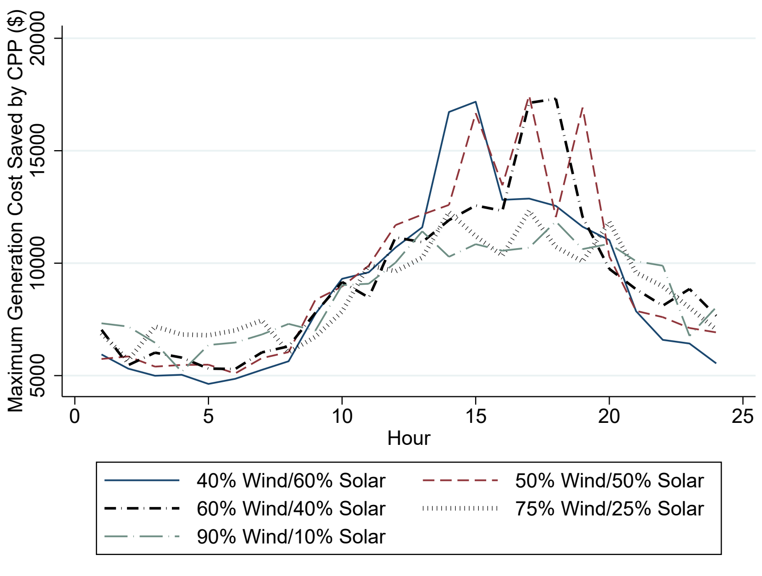

Maximum Generation Cost Saved by CPP ($)
5000
10000
15000
20000
0
5
10
15
20
25
Hour
40% Wind/60% Solar
50% Wind/50% Solar
60% Wind/40% Solar
75% Wind/25% Solar
90% Wind/10% Solar

Figure A.11