Appendix: For Online Publication

Making the Best of the Second-Best: Welfare Consequences of Time-Varying Electricity Prices

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A Peak Pricing Program Details

The PG&E peak pricing program was created in 2008. In 2010 and 2011, the regulator issued decision 10-02-032 and 11-11-008 respectively, which ordered that small and medium C&I customers be placed on opt-out peak pricing once they had sufficient hourly billing data available.[1] Prior to these decisions, peak pricing was structured as an optional opt-in program, but enrollment generally was low. The first wave of small and medium C&I customers were placed on the peak pricing tariff in November 2014. Customers were notified of their enrollment via mail and e-mail, and were given the ability to opt out easily at any time via a simple web interface. Appendix Figure A1 shows the letter that was sent to all establishments in October 2014 notifying them that they would be enrolled in November 2014 for the summer of 2015. The letter was one of many notifications sent, and includes clear directions on how to opt out of the program through their PG&E online billing interface.

Establishments are notified of a peak pricing event day by 2:00 pm the day before an event, and on Friday for Monday events. PG&E decides when to call an event day using the day-ahead maximum temperature forecasts at five National Weather Service (NWS) stations located in the inland regions of California.[2] When the average of maximum temperatures across all five stations exceeds a trigger temperature, typically 96 or 98 degrees, an event day is called for the following day.

Appendix Table A1 lists all of the event days between 2013 and 2015. The second column shows the forecasted average maximum temperature from the five NWS weather stations. The trigger temperature is based on historical weather patterns and is adjusted every 15 days throughout the summer. The trigger temperature starts at 96 degrees earlier in the summer and adjusts based on how many event days are called. For example, if many

[1] Large PG&E customers, defined as having demand charges above 200kW/month, were transitioned to opt-out peak pricing starting in 2010.

[2] Three day-ahead forecasts were used to call a Monday event day. The five stations used for the average are Red Bluff (KRBL), Sacramento (KSAC), Fresno (KFAT), Concord (KCCR), and San Jose (KSJC).

event days are called in the first part of the summer, the trigger will be revised upward to save the remaining event days for the hottest days.[3]

B Data Appendix

For this analysis, I combined PG&E data from many sources to create the final dataset for analysis. The high-frequency usage data required cleaning and a number of assumptions to collapse it down to the establishment level. The following section details the process of how I constructed the final dataset.

B.1 Interval Usage Data

PG&E first gave me interval usage data for a large sample of non-residential, non-agricultural establishments for 2010-2014. From this dataset, I requested the 2015 data for the subset of establishments that I use in my analysis. All of these establishments had smart meter interval data that started within 6 months of September 1, 2011, a date that I use in my identification strategy.[4] This gives me a dataset of electricity usage for 54,458 accounts in 2014 and 2015. The high-frequency usage data was collected from establishments at the 15 minute level, which I aggregate to the hourly level for analysis. From this point forward, the sample I discuss refers to hourly observations between 2:00 pm and 6:00 pm for all summer non-holiday weekdays (June-October) in 2014 and 2015.[5]

Using this initial dataset, I drop establishments that moved or changed ownership during the summer of 2014 or 2015. I do this because I want to focus the analysis on establishments that faced peak pricing for the full summer. This drops 10,231 establishments, leaving 44,227 in the balanced panel. I require that at least 23 percent of the establishments have non-zero usage over the 2014-2015 sample. This is done to guarantee that there is positive electricity consumption during most hours. This drops an additional 4,603 establishments, leaving 39,624.

I drop all establishments that never consumed 1 kWh in any peak hour, and I drop establishments that consumed less than 800 kWh/month during the summer of 2014. These requirements are to remove any smaller usage meters that may not be directly associated

[3]The goal of this approach is to be more stringent earlier in the summer when there is more uncertainty over the remaining weather of the summer.

[4]See Section 4.1 for more details on the identification strategy.

[5]I drop all establishments that voluntarily opted into the peak pricing program. More details on this can be found in Appendix Section D.4.

with an establishment's main electricity usage.[6] For example, there are cases where a meter was installed to power a single light in a strip mall, but was not associated with any of the establishments there. In some cases, the light was paid for by the owner of the strip mall and not by a business establishment, making it too small to consider in this analysis. The 1 kWh/hour restriction drops 5,145 accounts and the 800 kWh/month restriction drops another 14,224, leaving a dataset of 19,318.[7] Establishments that consumed more than 10,000 kWh/month in the summer of 2014 are also dropped due to their large size and the likelihood that they would graduate to a higher tariff in the near future. Only 272 establishments were excluded based on this criterion. Despite the large number of establishments dropped based on size restrictions, those that remain account for 82 percent of total electricity demand in this class of customers.

In many parts of the analysis, I break my sample into an inland and coastal region of the PG&E service territory. This is done because the coast has a milder summer climate, which may impact how establishments respond to peak pricing. To determine an establishment's region, I use the PG&E baseline territory designation. Baseline territories are defined as geographic areas that have similar weather conditions, making them an ideal way to geographically classify establishments. PG&E uses baseline territories for billing residential customers, but they have no impact on C&I electricity prices. I classify establishments in baseline territories Q,T and V as coastal, and the others as inland.

North American Industry Classification System (NAICS) codes were provided by PG&E for 89.2 percent of the establishments in the sample. Classifications are typically done at the firm level, meaning that the NAICS code assigned to a given establishment may not reflect its actual business. For example, the office space associated with a food packing plant may also be classified as a food packing plant due to the overall firm classification. Despite these limitations, it still provides useful information for the data cleaning process. Appendix Table A4 shows the breakdown of establishments by two-digit NAICS prefix. I drop meters with the two-digit prefixes 22 and 51 because they did not correspond to specific establishments, and typically had time-invariant consumption profiles in the pre-period. NAICS code 22 signifies "utilities," and, for small C&I establishments, it typically corresponds to irrigation systems run by city governments. They are generally small electricity users, and there are only 166 of these establishments in the dataset. The NAICS prefix 51 corresponds to the "information" industry classification, which, in my dataset, are cellular phone transmission towers run by companies such as AT&T and Verizon. The 702 establishments with this classification had

[6]This step is due to the fact that the data is provided at the account level, and must be aggregated to the establishment level. Some small usage accounts are not associated with an establishment, and are dropped in this step. Appendix Section B.2 discusses the establishment definition in more detail.

[7]The results are robust to including smaller establishments.

flat consumption profiles and were usually located in fields or on top of buildings. The results in this paper are robust to the inclusion of these two NAICS codes.

The final cleaned dataset contains interval usage data for 19,071 establishments in the summers of 2014 and 2015.

B.2 Classifying Establishments

I define an establishment as an electricity user at a single location where electricity bills are paid for by the same entity. This definition reflects the fact that some establishments have multiple electricity meters. PG&E interval usage data is reported at the meter-account level, which does not map directly to the establishment level that I use for analysis. The majority (83 percent) of establishments have one meter associated with each location, making the mapping of meter-account to establishment level data straightforward. Around 9 percent of the total establishments had multiple meters clearly at the same location, making it possible to collapse usage to the establishment level. Another 7 percent of customers have meters that may be at the same location, but where the smart meters were installed on a different date.[8] I do not aggregate across accounts such as this because it is possible that, at a given establishment, one meter may end up on peak pricing while the other does not. I include these meters as separate establishments in my analysis.[9]

The analysis in this paper focuses on small C&I establishments. Around 2.3 percent of establishments share a premise with a meter that is on a different price schedule (tariff). For example, the office space that administers a food processing plant may be the correct size to be in my sample. However, the food processing plant, which uses a lot more electricity, may be on a tariff designed for much larger users, and is not in my sample. To test for the impact of establishment classification, Appendix Table A6 shows the results when all of the ambiguously classified establishments discussed in this section are dropped. This leaves the 83 percent of establishments with a one-to-one relationship between the meter and the establishment. The results are similar to what is found using the primary specification in Table 3, suggesting that establishment classification has little impact on the estimated outcomes.

[8] In some cases, an establishment may have one smart meter that was installed within the eight-week bandwidth of September 1, 2011 and another that was not.

[9] The results are robust to specifications where these establishments are dropped.

C Time-of-Use Pricing

The regulator established a set of data requirements for all establishments before they were placed on opt-out peak pricing. The requirements were designed so that establishments would have a history of interval metering data before they were presented with a more complex, time-varying price. The data requirements are responsible for the September 1, 2011 threshold that is used to identify peak pricing program impacts in this paper.

The September 1, 2011 cutoff is due to two different, but related, requirements. First, establishments needed to be on mandatory time-of-use (TOU) pricing for two years before they were eligible for peak pricing. Second, establishments needed to be given a billing analysis by PG&E before they were moved onto mandatory TOU pricing. The billing analysis required a full year of data to conduct, and it told establishments how their bills would change under TOU pricing. The billing analysis had to be given to an establishment at least 45 days before it was placed on TOU pricing. The two requirements combined to require that an establishment had interval usage data before September 1, 2011 to be eligible for opt-out peak pricing in the summer of 2015.

Due to these requirements, the establishments that were placed on peak pricing in November 2014 are the same establishments that were placed on TOU in November 2012. At the time of peak pricing treatment in the summer of 2015, these establishments had been on the TOU rate for 2.5 years. The other establishments in my sample not on peak pricing were also on TOU pricing, but for only 1.5 years by the summer of 2015. Importantly, all establishments in my sample were on TOU pricing in both 2014 and 2015. However, the establishments on peak pricing had been on TOU pricing for one more year than the non-peak pricing establishments. If the extra year on TOU pricing impacted peak consumption, then it could bias the peak pricing impacts estimated in Section 5.

TOU pricing did not change electricity prices for small C&I establishments by a large amount. Before TOU pricing, small C&I establishments paid $.228/kWh during the summer months, regardless of when it was consumed. Once establishments were moved to TOU pricing, they paid a different price depending on the time of day. In the summer during the peak period, which runs between noon and 6:00 pm, electricity cost $.248/kWh. The off-peak price, which runs from 9:30 pm to 8:30 am, is only discounted to $.212/kWh.[10] The price difference between peak and off-peak consumption is small compared to other C&I customers. For example, large C&I establishments pay $.148/kWh for their peak electricity

[10]The part-peak rate, which runs from 8:30 am to noon and 6:00 pm to 9:30 pm, costs $.239/kWh. Establishments pay off-peak rates on weekends. These rates reflect prices during the summer. Prices during the winter are lower.

and a much lower \$.077/kWh for off-peak consumption.[11] The small price change for small C&I establishments suggests that it may not significantly impact peak consumption.

I empirical test the impacts of TOU prices on peak consumption by examining the impact during the first year it was rolled out. I leverage the same September 1, 2011 threshold used in the main identification strategy to estimate how TOU impacted peak usage. I compare establishments that were eligible for TOU in November 2012 to those that just missed the cutoff and were rolled over in November 2013. This design compares establishments in the first year of TOU to those that were still on flat-rate prices. I use the instrumental variables approach outlined in section 4.2 and look at the same 2:00 pm-6:00 pm window as in the peak pricing analysis. Establishments that were eligible for TOU in November 2012 are the same establishments that were eligible for peak pricing in 2015.

Appendix Table A7 shows the results of these TOU regressions. I conduct the analysis for both the full summer and for just the event days called that summer. The results across all of the specifications show that TOU did not significantly affect peak electricity consumption during the summer of 2013 when the program was first implemented. If TOU does not significantly change an establishment's consumption compared to the flat rate, then it seems unlikely that being on the tariff for 2.5 years versus 1.5 years would significantly affect usage. This result suggests that the differential time on TOU pricing did not impact peak consumption during the summers of 2014 and 2015.

C.1 Smart Meter Background

Analog meters have been used since the late 1800s to measure how much electricity an establishment consumes. These meters were read monthly by a "meter reader," a utility employee who manually checked an establishment's usage once a month. Analog meters are limited to tracking total kWh consumption, and for some customers they also measure peak monthly kW usage. Smart meters were first installed across the PG&E service territory starting in 2008. Smart meters automatically transmit meter-level usage data to PG&E via a wireless network, eliminating the need for manual checking, and allowing for the collection of high-frequency usage data.

Most PG&E establishments had smart meters as of mid-2013, with some residential customers remaining on analog meters by request. Smart meter installations require a utility worker to visit a business and swap out the old meter. A replacement typically takes 5-15 minutes, does not require the account holder to be present, and only results in a brief interruption in power. Smart meters were deployed across all parts of PG&E's service territory

[11] Electricity prices for large C&I establishments are smaller because they also pay daily fixed fees and demand charges based on monthly maximum demand.

simultaneously. Some parts of the state received a larger portion of the installs earlier in the deployment than others. For example, the California Central Valley had a larger portion of its meters upgraded to smart meters in the earlier years of the rollout.

Within each region of the state, the installations at individual establishments were as good as random. Conversations with employees at PG&E have indicated that the deployment pattern of smart meters was based on the availability of contractors and resources, and generally not related to establishment characteristics. A PG&E report on the deployment described:

> The deployment schedule is dependent upon the availability of a trained workforce, an effective supply chain to maintain an efficient installation process, and customer premise access to make the necessary changes at each service location. Deployment planning adjustments may be required due to any number of factors, including adverse customer impacts, supply chain considerations, labor availability, and technology considerations, which could affect the scheduling of meter endpoint installations (Pacific Gas & Electric 2010).

A smart meter transmits data wirelessly to PG&E through a series of network access points on utility poles throughout the PG&E service territory. After a smart meter is installed, it takes between 60 and 90 days for the meter to sync up with the network and for the data to become available in the PG&E system. Furthermore, a series of data quality checks is conducted by the PG&E system to verify that the data is of suitable quality for billing, and that there are no holes in the data. During this time period, the meter reader continues to manually check the usage on the smart meter to verify the transmission system worked as intended. Once this process is complete, the establishment is transitioned to full smart meter interval usage data collection. This process is summarized in the PG&E documentation as follows:

> After installation, gas and electric meters transition when: (1) the communications network infrastructure is in place to remotely read them; (2) the meters are installed, remotely read, and utilize smart meter data for billing; (3) and the remote meter reads become stable and reliable for billing purposes. Once enough customers on a particular "route string" transition to smart meter billing, manual reading of the meters on that "route string" ceases, and those meters are considered activated (Pacific Gas & Electric 2010).

This transition process explains why a large portion of the establishments that were eligible for peak pricing did not end up in the program for the summer of 2015. If an establishment did not have a full year of "stable and reliable" billing data to allow for a billing analysis to be conducted, then they were not moved to TOU pricing in November 2012. The interval meter start date data used in this paper reflects when the interval data was first collected, not when it was declared "stable and reliable." As a result, the eligibility status does not perfectly predict peak-pricing enrollment in the summer of 2015.

C.2 Regression Discontinuity Approach

This section introduces a fuzzy regression discontinuity (RD) approach that explicitly controls for the distance in days an establishment is from the September 1, 2011 threshold. I estimate the impact of peak pricing with the following two equations via 2SLS:

$$\begin{aligned} Q_{it} = \beta_1 \widehat{Peak}_{it} + \beta_2 X_i Post_t + \beta_3 X_i \{Eligible \times Post\}_{it} + \beta_7 Temp_{it} + \\ \beta_8 Temp^2_{it} + \zeta_t + \gamma_i + \epsilon_{it} \end{aligned} \tag{A1}$$

$$\begin{aligned} Peak_{it} = \alpha_1 \{Eligible \times Post\}_{it} + \alpha_2 X_i Post_t + \alpha_3 X_i \{Eligible \times Post\}_{it} + \\ \alpha_4 Temp_{it} + \alpha_5 Temp^2_{it} + \zeta_t + \gamma_i + \eta_{it} \end{aligned} \tag{A2}$$

Equation (A1) is the second stage equation. $\widehat{Peak}_{it}$ is an indicator of peak pricing enrollment for establishment i in hour-of-sample t, which is instrumented for in the first stage (Equation A2) using the cutoff-based instrument interacted with the post period. I control for the distance in days from September 1, 2011 linearly, using X_i, as suggested by Gelman and Imbens (2017). γ_i controls for establishment fixed effects.[12] The remaining terms are the same as those found in Section 4.2. Inference is complicated by the discrete nature of the distance from the threshold running variable. I cluster at the distance from threshold level based on the suggestion of Lee and Card (2008).[13]

The main difference between the RD approach and instrumental variables approach used in Section 4.2 is that the RD controls for the distance from the threshold in the post period.[14] This technique absorbs any linear relationship between the distance from the threshold and ϵ_{it}, which removes it as a potential confounding factor in the estimation of

[12] The results are robust to using an establishment by hour-of-day by day-of-week fixed effect.

[13] Individual establishments are nested within each distance from the threshold, meaning the errors are also robust to within-establishment correlation. See Appendix Section D.3 for alternate clustering specifications.

[14] The other terms that are typically seen in a cross-sectional RD such as overall distance from the threshold and a period indicator are absorbed in the panel RD framework by the establishment and time fixed effects. As a result, the only difference between the RD and IV approach is the post period indicator interacted with distance from the threshold.

peak pricing impacts. Identification in the RD model comes from the assumption that the relationship between ϵ_{it} and the distance from threshold does not change discontinuously at the September 1, 2011 cutoff, conditional on controls and fixed effects.

Figure A5 presents graphical evidence that the observable characteristics are smooth through the discontinuity. Another concern is the potential manipulation of the running variable near the threshold. I do not expect this to be a factor because the September 1, 2011 threshold was not known to the establishments or PG&E staff at the time. The top right graph in Figure A5 shows the count of smart meter installations by bin. There is no visible spike before or after the September 1, 2011 threshold, which is evidence that establishments did not manipulate their starting date.

The main RD specification uses the same sample as the IV approach, where establishments are restricted to have high-frequency metering data that started within eight weeks of the September 1, 2011 cutoff. In alternate specifications, I use varying bandwidths and find similar results.

D Results Robustness

D.1 Regression Discontinuity results

In this section I show the impacts of peak pricing on electricity usage using the RD approach in Section C.2. Table A8 shows the first stage results from estimating Equation (A2). Column (1) shows the results for the sample that spans the PG&E service territory. This first stage result is smaller than the coefficient estimate of .223 that was found using the IV approach. The discrepancy reflects the differences between the approaches: they are identifying different local average treatment effects (LATE). The RD approach estimates the vertical difference, conditional on fixed effects, at the September 1, 2011 cutoff, which is roughly 9 percentage points, as seen in Figure 3. The IV approach, on the other hand, estimates the average difference between eligible and ineligible customers, leading to a higher number. The F-statistic on the first stage approach is 24, providing evidence of a valid first stage. Columns (2) and (3) report the first stages for the coastal and inland regions separately. The result is not significant for the Coastal RD, suggesting that it is a weak instrument for that subset of customers.

Table A9 shows the impacts of peak pricing on electricity consumption. The sample is the same as the primary specification estimated in Table 3. Similar to the primary IV specification, the results for all PG&E and the Coastal region are not significant at the 5 percent level. Establishments in the inland region reduce their usage during event hours by

24.6 percent. The impact of peak pricing on inland establishments using the RD approach is larger than the 13.5 percent reduction found in the primary specification. This difference reflects the different local average treatment effects estimated by the two approaches. The RD specification estimates the treatment effect at the September 1, 2011 cutoff, while the IV approach estimates the average impact across the entire 8 week sample. Despite the large difference in the point estimates, it is not possible to reject that the two estimates are the same.

Figure A6 graphically shows the intent-to-treat impacts of peak pricing eligibility on peak usage using the RD approach for inland customers. The horizontal axis bins customers by when their smart meter data were first collected, similar to Figure 3. The vertical axis displays the difference between average 2015 event day consumption and 2014 event day consumption. The figure presents residuals after temperature, establishment, and hour-of-sample fixed effects are removed. Customers to the right of the September 1, 2011 cutoff were not on peak pricing, while a portion of customers to the left of the vertical line were on peak pricing. The figure shows a reduction in peak consumption for peak-pricing-eligible establishments to the left of the vertical line compared to the ineligible group to the right.[15] The intent-to-treat impacts of peak pricing seen in this figure are visible but noisy.

The RD approach uses an eight-week bandwidth around the September 1, 2011 cutoff, but the results do not change substantially at different bandwidths, as shown in panel B of Figure A7. The results in this section are robust to a number of other specification and clustering choices, as shown later in this section.

D.2 OLS Results

Appendix Table A11 shows the results for the IV approach run with OLS. This approach uses the 13 percent of establishments on peak pricing as the treatment group and the 87 percent not on peak pricing as the control group. The results are smaller than what was found using the IV approach. This is consistent with a story that the control group was reducing its usage between 2014 and 2015, which would result in a lower treatment effect. It is also likely that the treatment and control groups are not balanced on unobservable characteristics that may impact peak consumption. The research designs used in this paper avoid the potential for bias in the OLS results by using a natural experiment to compare similar peak-pricing eligible and ineligible establishments.

[15] I remove Monday event days from the figure because they typically have a noisier response due to being announced the Friday before. By removing Mondays, it is easier to see the effects in Figure A6.

D.3 Clustering Robustness

This section considers an alternate way to cluster the standard errors in this analysis. In the main analysis, errors for the IV specification are two-way clustered at the establishment and hour-of-sample level. In the RD specification, errors are clustered at the distance from threshold level. One alternative is to cluster errors at the weather station level. The hourly weather data comes from 297 weather stations across Northern California, with establishments matched to the closest station.[16] Establishments are matched to the same weather station for the full sample, meaning the establishment clusters are contained within each weather station cluster.

Appendix Table A12 shows the results with errors clustered at weather station level. For the IV specification, I two-way cluster at the weather station and hour-of-sample level. In the RD specification, I two-way cluster at the distance-from-threshold and weather station level. The results show that this higher level of clustering has little impact on the standard errors, and it does not impact the overall results.

D.4 Opt-in Establishments

In the primary analysis in this paper, I do not include establishments that voluntary opted into the peak pricing program. I do this because the establishments opted into peak pricing at various times throughout 2014 and 2015. As a result, they were on peak pricing for a different length of time than the majority of establishments in my sample. 48 of the 234 establishments that opted into peak pricing did so before the summer of 2014, meaning they did not have bill protection in the summer of 2015. Another five establishments chose to enroll in peak pricing during the summer of 2015. The remaining 181 establishments enrolled in peak pricing in April and May of 2015. This gave them less time to prepare for the peak pricing program than the establishments that had been automatically enrolled in November 2014.

I include the opt-in establishments as a robustness check to test whether their presence impacts the results. Appendix Table A13 shows the main specification estimated with the 234 opt-in establishments included. The results show that including these opt-in customers has a small impact on the overall results. Column (6) shows that the inland RD specification is no longer significant at the 5 percent level, but the point estimate does not change much. The inland IV estimate has a coefficient of -.1375, which is smaller than the coefficient of -.1451 in the primary results. I cannot reject that these two values are the same, suggesting that opt-in establishments do not have a large impact on the results.

[16] I use a balanced panel of weather stations, and no weather stations enter or leave during the sample.

E Calculations

E.1 Calculating PG&E Wide Savings Estimates

This section provides details on the PG&E-wide savings calculations discussed in Section 5.5. PG&E does not release data that reports peak load by customer class. To proceed with the calculations in this section, I make a number of informed assumptions about the consumption patterns of small C&I PG&E customers.[17]

First, I calculate the total number of inland establishments on the A1 tariff based on demographic data provided by PG&E. I adjust this number downward to reflect the fact that my sample includes only customers that consumed between 800 kWh/month and 10,000 kWh/month during the summer months.[18] This results in 157,000 inland establishments that are like those I study in my analysis. I adjust for establishments that will opt out of peak pricing by using the PG&E-wide observed opt-out rate for small C&I establishments between November 2014 and October 2016 of 16.7 percent. I assume subsequent waves of establishments will opt out at the same rate.

To calculate the average establishment level kWh/hour reductions, I multiply the average inland establishment consumption of 6.7 kWh/hour by the implied percent reductions from Column (3) of Table 3. To calculate the aggregate impact, I multiply this by the number of inland establishments that satisfy the criteria outlined above. Using this approach, I find that small C&I establishments provide reductions of 118 MW.

This calculation assumes that the establishments used in the main estimation sample reflect the average consumption patterns for all C&I establishments. It is not possible to prove that the local average treatment effects estimated in the previous sections reflect the behavior of all small C&I establishments in California, but the estimates are the best available and are useful for back-of-the-envelope calculations. Figure A8 shows that this is true when comparing establishments within 8 weeks of the September 1, 2011 cutoff to those within 27 weeks. It shows a similar pattern of usage, helping to validate this assumption.

The aggregate savings estimate calculated above is conservative in nature. I am considering only the savings for inland customers with summer consumption between 800 kWh/month and 10,000 kWh/month. This leaves out a large number of smaller establishments, and a small number of larger establishments that likely reduce their usage under peak pricing. The savings estimate also does not include reductions from coastal customers. I make this

[17] I cannot use my interval consumption data to make these calculations because I only have a sample of small C&I establishments' usage.

[18] I do this using the ratio of inland establishments consuming between 800 kWh/month and 10,000 kWh/month to all inland establishments in my sample.

choice because the main empirical strategy did not find significant reductions for the coastal establishments.

E.2 Environmental impact

The peak pricing program is designed to improve grid efficiency, but it also affects power plant emissions. In California, peak demand is typically satisfied by natural gas turbine generators, which have a moderate CO_2 emissions rate and low SO_2 and NO_X emissions rates. To better understand the magnitude of the impacts of peak pricing on CO_2 emissions, I conduct a simple back-of-the-envelope calculation using my estimates of the impact of peak pricing on demand along with estimates from the California Energy Commission on emissions rates (California Energy Commission 2015). I find that the peak pricing program will cause a reduction of around 4,000 metric tons of CO_2 per summer when the policy is fully implemented.[19] The calculation also assumes that the peak pricing program will not increase consumption during non-event hours. The annual reduction in CO_2 emissions, while not insignificant, is only .11 percent of California's daily electricity sector emissions (California Air Resources Board 2019). Using a $50/ton social cost of carbon, the reductions translate to around $200,000 per year in benefits (Revesz et al. 2017).[20] I include these benefits in the welfare calculations conducted in the subsequent section. Overall, the carbon reduction benefits are a small fraction of the overall value provided by the peak pricing policy.

E.3 Detailed Calculations of PG&E Welfare Impacts of Peak Pricing

In this section, I calculate the welfare impact of the PG&E peak pricing program for small C&I establishments using the model from the previous section and my empirical results. The calculations are summarized in Table 8. Some of the simplified assumptions in the model are adjusted to better reflect the PG&E service territory. In the model, the utility purchases

[19] This is a relatively small CO_2 reduction compared to California's total emissions of 440 million metric tons in 2015 (California Air Resources Board 2019). This calculation of the peak pricing program's effect is made using the CO_2 emissions rate of 1,239 lbs/MWh from a conventional single cycle plant. This is a conservative assumption because the other generation options, such as a combined cycle plant or hydropower, have lower or zero emissions rates. The use of hydropower to meet peak demand, while causing no emissions at the time of generation, has an opportunity cost that likely will lead to non-zero emission impacts in the long run.

[20] The impacts on SO_2 and NO_X are small enough that I do not include them in the benefits calculations. For example, I find that peak pricing will reduce NO_X emissions by less than 1 ton per year and SO_2 emissions by .05 tons. California's carbon emissions are capped, but the cap is not currently binding. As a result, any additional emissions reductions from peak pricing will reduce total emissions. If the cap is binding in future years, the welfare benefits from reducing carbon emissions will be lower.

capacity yearly at cost $C(X_t)$. In practice, the peaker plants that are used to satisfy peak demand typically last at least 30 years.

To approximate the cost function, I use the construction cost of a single cycle peaker plant. The California Energy Commission estimates it costs \$1,185,000/MW to build a natural gas combustion turbine peaker plant (California Energy Commission 2015).[21] Using these plant construction numbers and my empirical estimates, I find that the peak pricing program would provide a one-time saving of \$140 million in construction costs. I assume this cost savings occurs in year 1 of a 30-year program. To value the total impacts of the program, I include the discounted stream of annual costs and benefits. Reducing peaker capacity provides an annual benefit of avoided staffing and maintenance costs, which in this case totals \$3.07 million per year. I use a linear demand curve to make the net consumer surplus (CS) and utility surplus (UTS) loss calculation. I find the CS losses are \$2.05 million per year, and the UTS losses are \$1.11 million per year.

The PG&E peak pricing program gives enrolled establishments a \$.01/kWh discount on all non-event day electricity consumption. As a result, establishments will consume more electricity in off-peak hours, resulting in increased consumption across almost all summer hours. Importantly, this price reduction is welfare improving because the retail price of electricity for small C&I customers exceeds any reasonable social cost. The benefits of the \$.01/kWh discount are small but add up across all non-event hours during the summer. Using my elasticity estimates and linear demand, I calculate these welfare gains to be \$0.84 million/year.[22] The benefit of this small price decrease in non-event hours are added to the overall welfare benefits of the policy.

To come up with a total welfare value, I take the construction costs and add on the discounted stream of costs and benefits detailed above. I also include the benefits of reducing CO_2 emissions calculated in Section E.2, which total \$.2 million/year.[23] This results in total welfare benefits of \$159 million (2016 dollars) using a 3 percent real discount rate and a 30-year horizon.[24]

[21] All values used in this paper are in 2016 dollars. Original 2011 values are inflated using the IHS North American Power Capital Costs Index.

[22] This is a strong assumption because I am applying my demand curve estimates, derived for the period between 2:00 pm and 6:00 pm on event days, to all other hours in the summer. Using the empirical analysis on non-event hours in the summer of 2015, I can reject the level of responsiveness I am using for this calculation. Ultimately, the response from the off-peak CS gains is small and does not significantly impact outcomes.

[23] The local air pollution benefits are not significant and I do not include them in the calculation.

[24] The results are not sensitive to discount rate assumptions because most of the benefit is incurred upfront with the avoidance of capital construction costs. The other annual costs and benefits are roughly offsetting.

E.4 Assumptions for Comparison of Peak Pricing to Real-time Pricing

This section describes the assumptions used to make the calculations in Section 6.5. I compare the outcomes under peak pricing to the first-best outcomes under a theoretical real-time price scenario. I do this for two reasons. First, there is no market price in California that can be used for the real-time price comparisons. The existing wholesale market has a number of distortions, including a price cap, a capacity market and the regulator resource adequacy requirements. The price cap prevents the real-time price from going above \$1.00/kWh. The capacity market allows the utilities to use bilateral contracts to secure capacity, which further reduces the wholesale real-time price. All of these distortions make it problematic as a real-time price for this analysis, because it is not always clear what the California real-time wholesale price reflects. Second, the simple setup that I use allows for a transparent comparison between peak pricing and real-time pricing that does not depend on institutional details of the California market.

The theoretical market I use is structured as an energy-only market without any price caps. I assume real-time prices (RTP) take on two values. The low value is set at \$.10/kWh, which roughly reflects the marginal cost of a natural gas combined-cycle generator. The high value is set at \$1.35/kWh and reflects both the generation and capacity cost of peaker plants.[25] I assume prices spike to the high level sometime between 2:00 pm and 6:00 pm on three super-peak days per year. Customers are charged a monthly fixed fee to recover the remaining fixed costs associated with transmission and distribution. For the primary specification shown in Table 11, I assume prices are at the high level for one hour on each of the three super-peak event days. Appendix Table A16 considers an alternate scenario where prices are at the high level for the full four hours between 2:00pm and 6:00pm on the three super-peak event days each year.

Retail prices under peak pricing are similar to the real-time price for most hours of the year. Retail prices are set at the same \$.10/kWh price and fixed monthly charges are used to recover any remaining costs, including capacity costs, transmission and distribution charges. On event days, the price is raised between 2:00 pm and 6:00 pm. In the current program, I assume the price is set at \$.85/kWh for 15 event days each summer. For the well-targeted program, I assume a price of \$1.35/hour for eight event days per year based on the 101 degree trigger temperature described in section 6.4. In both cases, three of the event days are super-peak days each summer. By design, the peak pricing program will collect more

[25] The \$1.35 value is based on the large C&I peak price. PG&E based this value on its internal valuation of capacity.

revenue than the RTP program because of the longer and more frequent periods at the high price. I assume this money is reflected in adjustments to fixed charges for the subsequent year.

F Welfare Robustness Checks

Section 6.5 compares peak pricing to the first-best real time pricing policies. Embedded in this analysis are a number of assumptions about how establishments will respond to both real-time pricing and peak pricing. In this section, I consider a number of alternate scenarios to test the robustness of the results to changing some of these assumptions.

One important modeling assumption is that establishments respond in the same way to a peak pricing event announced a day in advance and a real-time price that changes on short notice. It is possible that the day-ahead alert gives establishments more time to prepare and could result in larger reductions in peak usage than a real-time price spike. To test the sensitivity of the results to this assumption, I consider a scenario where the demand reductions under real-time pricing are 15 percent smaller than those of peak pricing at the same price level. I find that the current peak pricing program achieves 51 percent of the first-best benefits and the well targeted version improves this outcome to 97 percent. The results reflect that if establishments are more responsive to peak pricing than real-time pricing at the same price level, the peak pricing program's relative performance improves. The decrease in establishment response to real-time pricing does not change the overall conclusion that a well-designed peak pricing program can greatly improve outcomes.

Another assumption is that the peak price should be set at $1.35/kWh. This level is based on a PG&E valuation of capacity, but it may not reflect the true long-run cost of supply. I test the robustness of the results to this assumption by rerunning the model using a peak price of $1.10/kWh. At this lower peak price, the current program would achieve 57 percent of the first best benefits and the well targeted version would achieve 88 percent.[26] The similarity of these results to the main specification shows that within a reasonable range, the overall findings are not sensitive to the level of the optimal peak price.

One shortcoming of the stylized welfare model is that net consumer surplus losses are calculated based on observed changes in consumption during peak pricing events. Any behavior undertaken by establishments before or after a real-time price spike or outside a peak pricing event window is not included in the net consumer surplus loss calculations. For this

[26] I find a similar result at optimal peak prices higher than $1.35/kWh, however this requires extrapolating the empirical results further out of sample than the main specifications and the results must be considered in this context.

omission to have a large impact on the results of the benchmarking exercise, establishments would have to respond differently to peak pricing than to real-time pricing in the hours outside the event window. For example, the longer peak pricing event window could cause establishments to adjust their behavior outside the event window more than they would under real-time pricing. If establishments behaved in this manner, the estimates in this section would inflate the value of peak pricing relative to real-time pricing. To test how a differential response might affect the results, I consider a scenario where the net consumer surplus losses are 50 percent larger under the peak pricing program. Using this altered assumption, the current and well targeted programs would achieve 39 percent and 75 percent of the first-best outcomes respectively. The findings suggest that higher peak pricing consumer surplus losses would reduce the relative effectiveness of the peak pricing program, but that there are still significant benefits to effectively designing the program.

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Appendix Figures

Appendix Figure A1: 30 Day Notification of Peak Pricing Enrollment

21PDPDEFLT2
PDP Final Default Letter (Ltr #3c)

Page 1 of 2

Important information regarding your transition to a Peak Day Pricing electric rate plan. Please read to learn more.

<<DATE>>

[Customer Name1]
[Customer Name2, if exists]
[Mailing Address2, if exists]
[Mailing Address1]
[Mailing Address City, State Zip]
[Mailing Address Country1]

Re: 30 Day Notification of Switch to Peak Day Pricing Electric Rate Plans for Business

Dear [Customer Name]:

Last month, we sent a letter to notify you that starting in November, one or more of your business accounts is scheduled to transition from a time-of-use electric rate plan to a Peak Day Pricing rate plan. This is part of a requirement by the California Public Utilities Commission to encourage conservation when energy demand is higher. This is a reminder of the upcoming move to a new electric rate plan.

Peak Day Pricing works in conjunction with your existing time-of-use rate, applying higher energy prices on 9 to 15 Event Days per year in exchange for discounted energy rates at all other times from May 1st through October 31st.*

This rate plan transition will affect the Service ID(s) referenced on the following page(s).

Peak Day Pricing includes automatic Bill Protection
Bill Protection lets you try Peak Day Pricing risk-free for a full year. After 12 months, we will compare your costs on Peak Day Pricing to what your costs would have been on your time-of-use rate plan. If your costs on Peak Day Pricing are higher, you will automatically receive a bill credit for the difference. You can opt out and return to your time-of-use rate plan at any time.

Make your decision today
PG&E is here to help you understand this new rate plan and decide what is best for your business. A personalized rate analysis can help you estimate how your electric bills may change with Peak Day Pricing.

- Access your online rate analysis anytime at **pge.com/myrateanalysis**

If you want to enroll early, or opt-out of the transition to Peak Day Pricing you can do so before your eligible Service ID(s) are automatically enrolled in November.

- Enroll early, or opt out of transition by visiting **pge.com/pdpchoice**

Update your notification preferences
If you plan to enroll, or have already enrolled in Peak Day Pricing, please be sure to update your Peak Day Pricing notifications, so you don't miss any Event Day notices. Update your notifications at **pge.com/myalerts**.

We value you as a customer and understand you may have some questions. For more information about the transition to Peak Day Pricing, visit **pge.com/pdp30day**.

Sincerely,

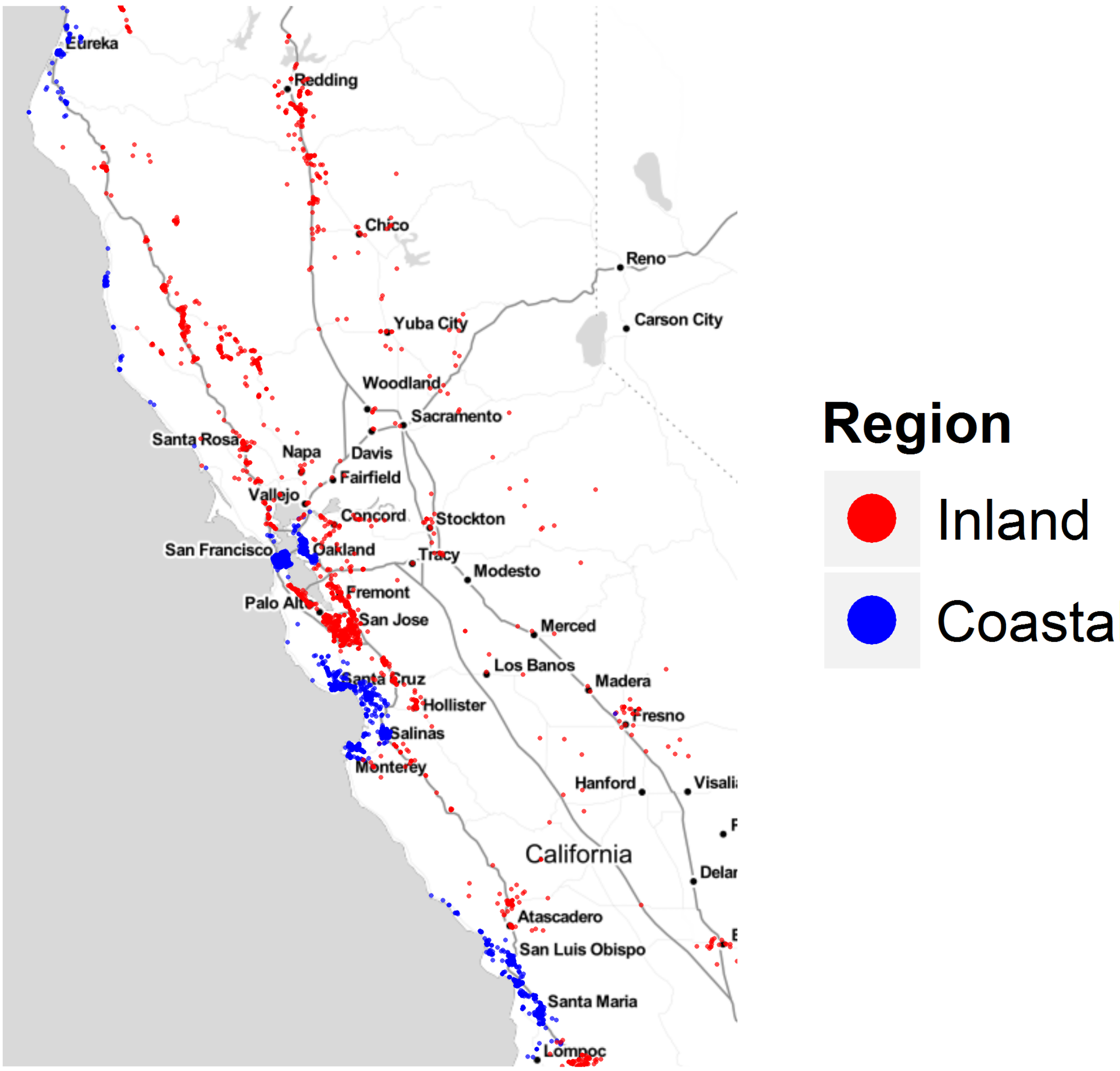
Maril Pitcock
Director, Pricing Products
Pacific Gas and Electric Company

P.S. Remember to stay away from downed power lines and never touch or try to move them. Always assume a downed power line is live and report them immediately by calling **911** and PG&E at **1-800-743-5000**.

* Effective summer rates are lower after Peak Day Pricing credits have been applied, but effective rates are higher during Peak Day Pricing Event Hours. "PG&E" refers to Pacific Gas and Electric Company, a subsidiary of PG&E Corporation. ©2014 Pacific Gas and Electric Company. All rights reserved. 21PDPDFLT2

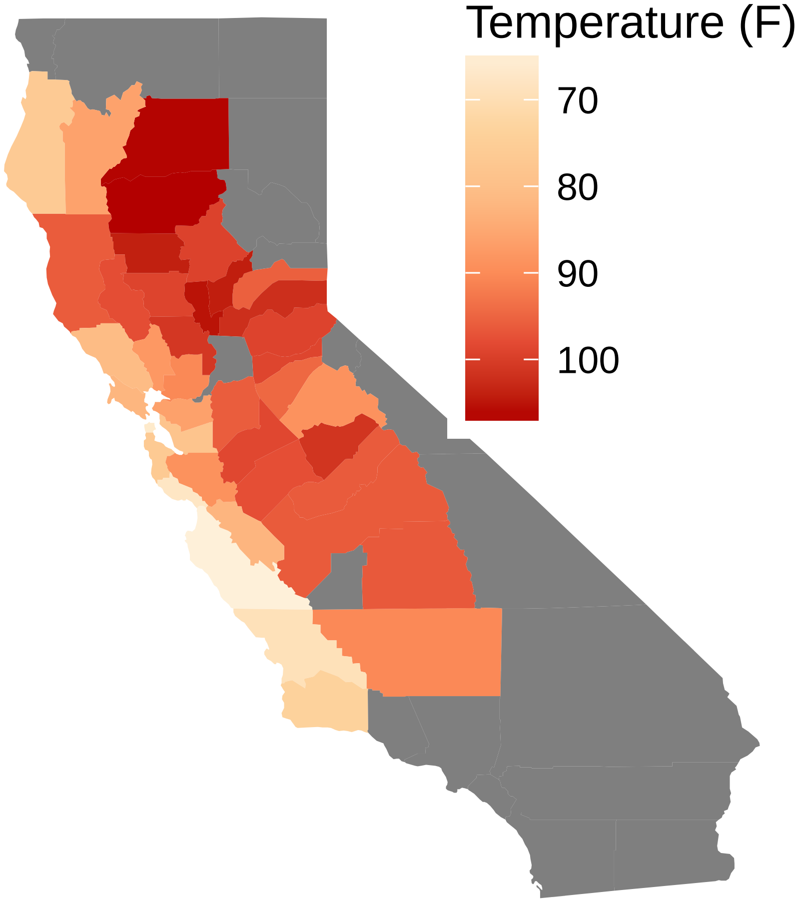
Note. — This letter is a sample of what was sent to every establishment 30 days before they were enrolled in peak pricing in November 2015. It was provided to me by PG&E. It was one of many letters that were sent to establishments informing them of the rollover. It provides information on how to opt out at the web site "pge.com/pdpchoice." It also describes bill protection and directs establishments how to set their event day notification preferences.

Appendix Figure A2: Map of Establishments in Primary Sample by Region



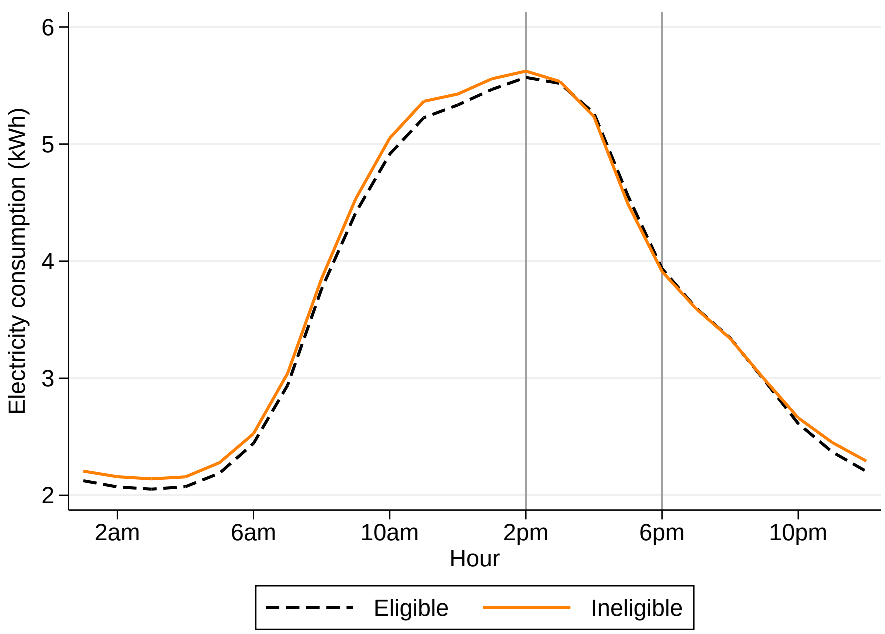
Note. — This figure shows all 7,435 establishments in the primary sample that have smart meter data starting within eight weeks of the September 1, 2011 threshold. Each dot corresponds to an individual establishment. The inland versus coastal designation is based on baseline territory as defined by PG&E and reflects climate conditions. See Appendix Section B.1 for more details on this classification.

Appendix Figure A3: Average Temperature on Event days by County



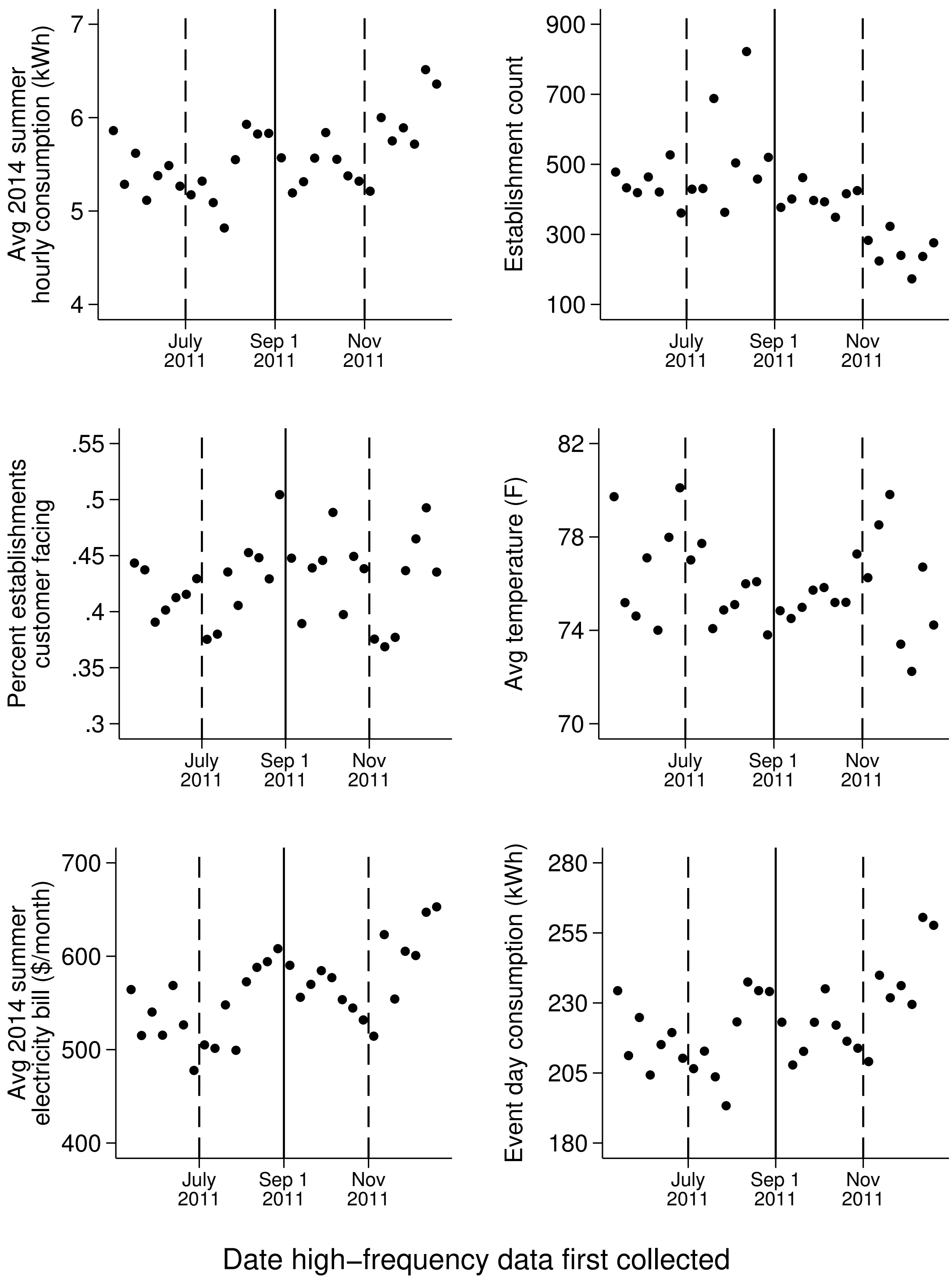
Note. — This figure shows the average temperature on event days in 2015 displayed at the county level. Temperatures reflect the average temperature across all Mesowest weather stations in a county between 2:00 pm and 6:00 pm. Weather stations are weighted based on the number of establishments to which they are distance-matched in the main analysis. Information is displayed at the county level as a convenient level of aggregation; county-level data is not used for any of the analysis in this paper. Counties in dark gray do not have any PG&E establishments. The figure shows that inland regions of California have much higher event day temperatures than do coastal regions.

Appendix Figure A4: Pre-Period Electricity Consumption by Eligibility Group



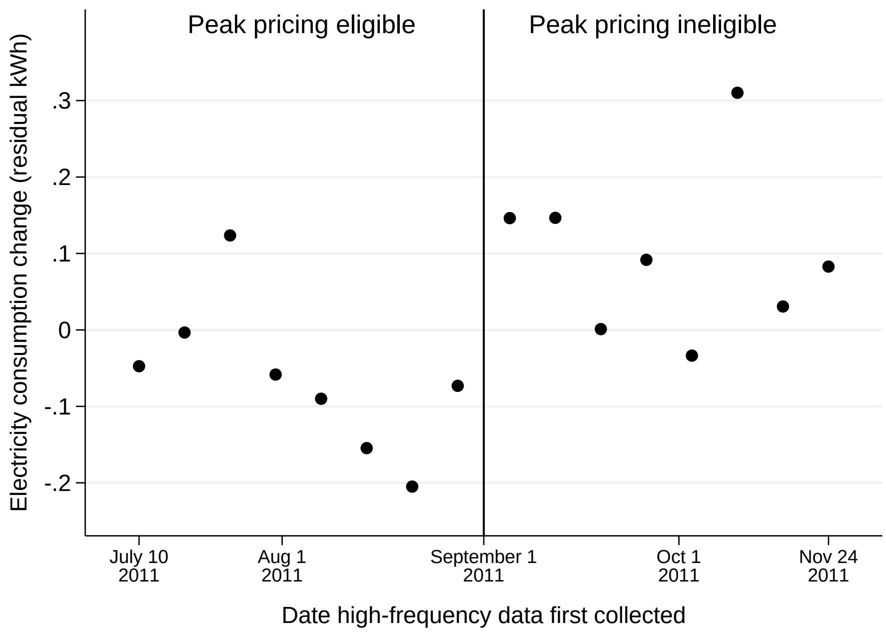
Note. — This figure shows the 2014 pre-period average hourly electricity consumption for peak pricing eligible and ineligible establishments. The vertical lines signify the beginning (2:00 pm) and end (6:00 pm) of the peak event window.

Appendix Figure A5: Smoothness of Observable Characteristics through the September 1, 2011 Threshold



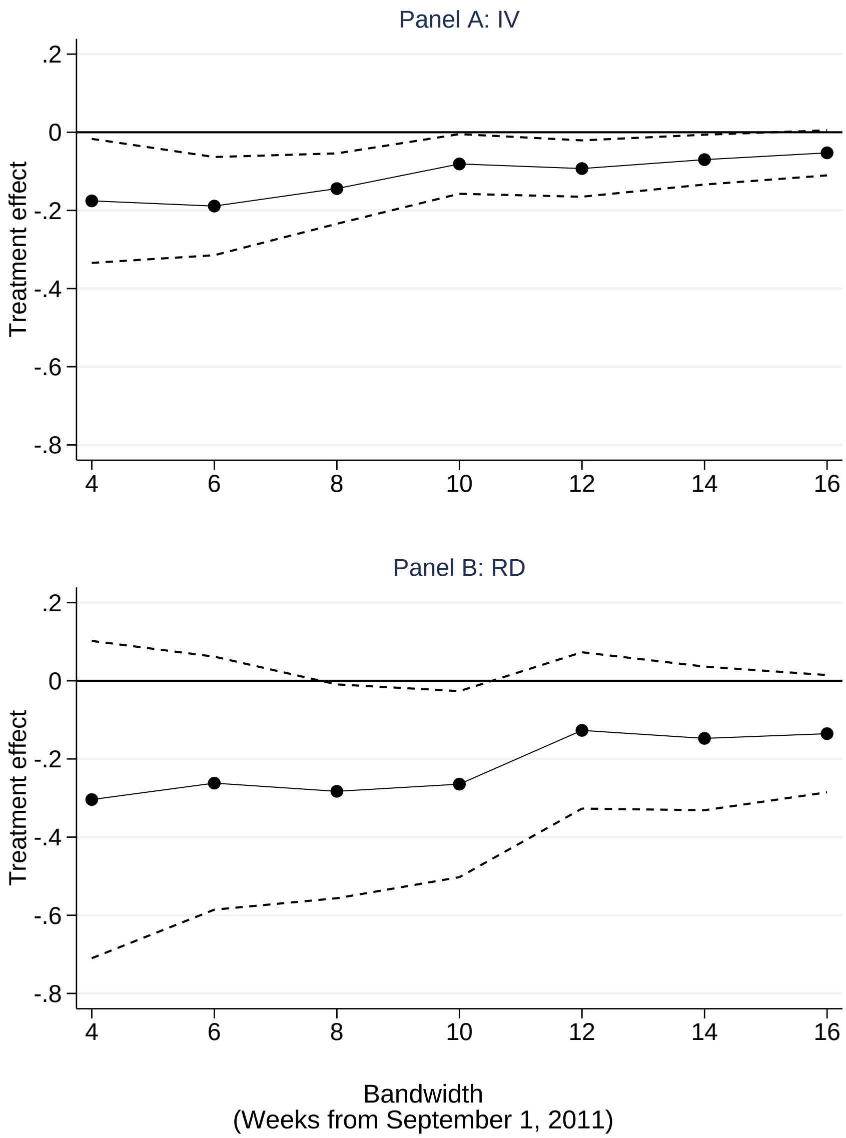
Note. — This figure shows trends in observable characteristics near the September 1, 2011 discontinuity, shown with the solid black vertical line. The vertical dashed lines indicate the eight-week bandwidth used in the main specifications.

Appendix Figure A6: The Impact of Peak Pricing Eligibility on Inland Establishment Peak Consumption (Intent to Treat)



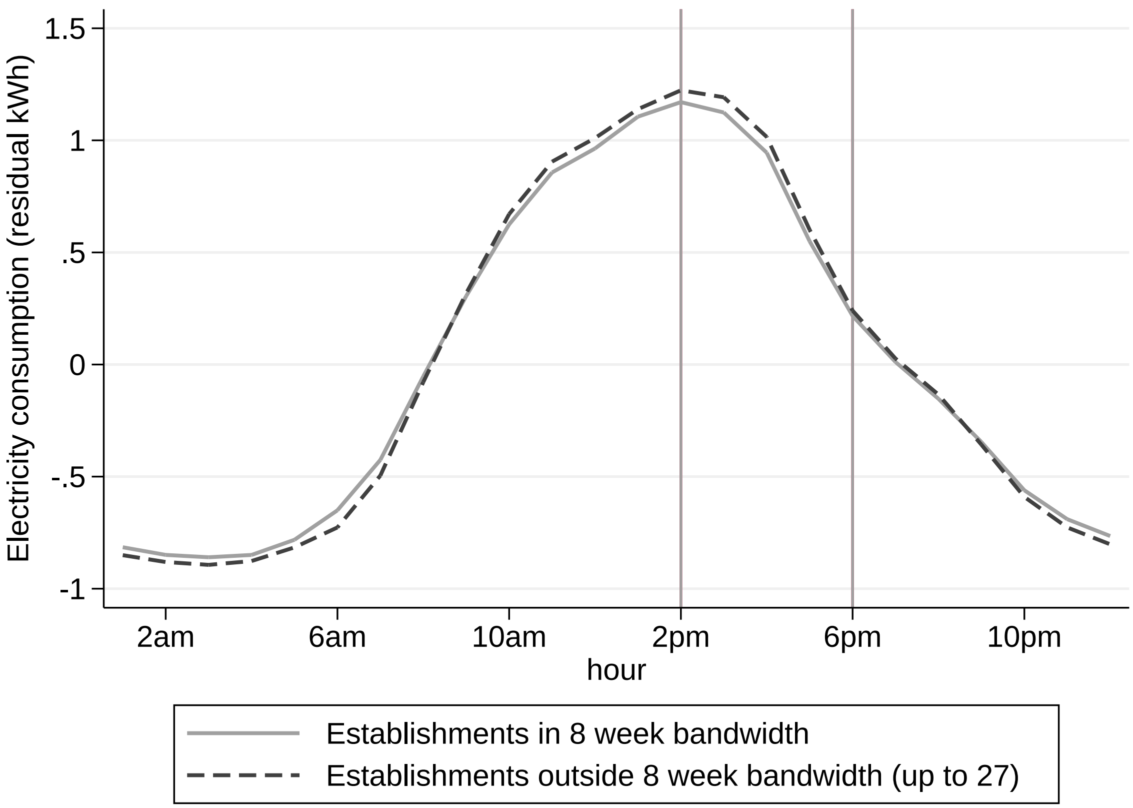
Note. — This figure shows the intent-to-treat impact of peak pricing eligibility on consumption between 2:00 pm and 6:00 pm on event days. Each dot represents the difference between 2015 and 2014 peak consumption by bin, conditional on establishment and hour-of-sample fixed effects. The figure shows the intent-to-treat impacts of the peak pricing policy, which is 6.2 percent and is significant at the 5 percent level. Establishments to the left of the September 1, 2011 cutoff are eligible for peak pricing and show a reduction in peak usage.

Appendix Figure A7: Treatment for Inland Establishments Effects Estimated at Varying Bandwidths



Note. — Each panel on this figure shows the coefficient from seven different regressions estimating the impacts of peak pricing on usage. Each dot represents an individual regression. Panel A shows the results from estimating Equation (1) for inland establishments using bandwidths between 4 and 16 weeks from the September 1, 2011 threshold. Panel B does the same using the RD specification from estimating Equation (A1). The dotted lines are the 95 percent confidence interval.

Appendix Figure A8: Pre-Period Electricity Consumption for Primary and Extend Sample



Note. — This figure compares summer 2014 hourly kWh usage for establishments in the primary sample of eight weeks from the September 1, 2011 threshold to a larger sample. The larger sample includes all establishments within 27 weeks of the September 1, 2011 threshold, excluding those within eight weeks. Values show residuals after establishment fixed effects are removed. The figure shows that the load profile is similar between the establishments used in the primary analysis and those further from the September 1, 2011 threshold.

Appendix Tables

Appendix Table A1: Event Days with Day Ahead Temperature Forecasts

Event date	NWS day ahead max temperature forecast	Trigger temperature
6/7/2013	98	96
6/28/2013	99	96
7/1/2013	107	96
7/2/2013	106	96
7/9/2013	96	96
7/19/2013	98	98
8/19/2013	94	96
9/9/2013	97	94
9/10/2013	94	94
10/18/2013	82	89
6/9/2014	100	96
6/30/2014	102	96
7/1/2014	96	96
7/7/2014	101	96
7/14/2014	99	96
7/25/2014	101	96
7/28/2014	97	96
7/29/2014	97	96
7/31/2014	98	96
9/12/2014	96	98
6/12/2015	99	96
6/25/2015	103	96
6/26/2015	100	96
6/30/2015	101	96
7/1/2015	100	98
7/28/2015	101	98
7/29/2015	104	98
7/30/2015	100	98
8/17/2015	101	96
8/18/2015	96	96
8/27/2015	97	96
8/28/2015	96	96
9/9/2015	102	98
9/10/2015	104	98
9/11/2015	101	98

Note. — This table shows all of the event days between 2013 and 2015. The second column shows the day-ahead maximum temperature forecast used by PG&E to call an event day. NWS corresponds to five National Weather Service stations that PG&E uses for its forecasting. The third column shows the trigger temperature that is used to call an event day. When the NWS forecast equals or exceeds the trigger temperature, an event day is typically called. The trigger temperature starts at 96 degrees earlier in the summer and adjusts based on how many event days are called.

Appendix Table A2: Average Outdoor Temperature on Event Days

Event date	All PG&E average temperature	Coastal establishments average temperature	Inland establishments average temperature
6/9/2014	74.76	67.01	91.66
6/30/2014	75.79	68.05	92.67
7/1/2014	71.28	64.92	85.15
7/7/2014	73.26	66.89	87.15
7/14/2014	73.49	66.85	87.99
7/25/2014	80.98	74.76	94.54
7/28/2014	76.67	71.12	88.77
7/29/2014	76.93	70.71	90.41
7/31/2014	76.00	68.85	91.58
9/12/2014	75.55	68.69	90.50
6/12/2015	75.03	67.57	91.29
6/25/2015	77.30	70.18	92.81
6/26/2015	72.94	65.12	89.98
6/30/2015	81.08	73.57	97.44
7/1/2015	75.89	69.38	90.05
7/28/2015	80.86	74.34	95.06
7/29/2015	77.21	69.55	93.90
7/30/2015	76.86	70.50	90.69
8/17/2015	77.94	70.66	93.77
8/18/2015	75.65	70.37	87.14
8/27/2015	83.97	80.18	92.21
8/28/2015	82.88	78.52	92.38
9/9/2015	86.73	81.66	97.77
9/10/2015	82.79	76.54	96.40
9/11/2015	80.62	74.40	94.17
Average	77.70	71.21	91.82

Note. — This table shows the average temperature between 2:00 pm and 6:00 pm on all event days in 2014 and 2015. The values reflect the outdoor temperatures using Mesowest weather station data. Average temperatures are weighted by the number of establishments that are matched to a given weather station. Temperatures do not reflect official National Weather station temperatures used to call event days. The data show that inland temperatures during event hours are much higher than coastal temperatures.

Appendix Table A3: Electricity Consumption of Establishments by Peak Pricing Eligibility Status in 2015

Variable	Ineligible	Eligible	P value of difference
Summer 2015 avg peak hourly consumption (kWh)	5.66	5.66	.96
	(4.41)	(4.47)	
Summer 2015 max peak hourly consumption (kWh)	8.99	9.07	.58
	(6.52)	(6.54)	
Summer 2015 total event hours consumption (kWh)	339	339	.97
	(264)	(268)	
Summer 2015 total non-event hours consumption (kWh)	12,226	12,083	.49
	(9122)	(8892)	
Establishment count	3,220	4,215	

Note. — This table shows the mean and standard deviation of the observable characteristics by peak pricing eligibility status for establishments within eight weeks of the September 1, 2011 threshold. Standard deviations are shown in parentheses.

Appendix Table A4: Establishment Industry Classifications

Naics 2 digit code	Establishment count	Percent of establishments
11	104	1.4%
23	232	3.1%
31	168	2.3%
32	107	1.4%
33	226	3%
42	224	3%
44	749	10%
45	286	3.8%
48	73	.98%
52	213	2.9%
53	650	8.7%
54	307	4.1%
56	157	2.1%
61	106	1.4%
62	655	8.8%
71	131	1.8%
72	1,068	14%
81	963	13%
92	215	2.9%
Not available	801	11%

Note. — This table shows the first two digits of the North American Industry Classification System (NAICS) industry classification for all 7,435 establishments in the sample. These two-digit NAICS codes are used to classify establishments as customer-facing or non-customer-facing in Section 5.4. The two-digit NAICS code is used because a large portion of establishments did not have more detail below that level. The PG&E data did not have NAICS code information for the 11 percent of establishments classified as "Not available."

Appendix Table A5: PG&E System Peak Demand Days

Date	Event day	PG&E max load	Hour of max load
8/17/2015	yes	19,451	4pm-5pm
6/30/2015	yes	19,320	4pm-5pm
7/29/2015	yes	19,248	4pm-5pm
8/28/2015	yes	19,233	4pm-5pm
9/10/2015	yes	19,230	4pm-5pm
9/9/2015	yes	19,017	4pm-5pm
7/20/2015	no	18,546	4pm-5pm
6/8/2015	no	18,441	6pm-7pm
7/28/2015	yes	18,403	5pm-6pm
9/21/2015	no	18,398	4pm-5pm
8/27/2015	yes	18,328	4pm-5pm
8/16/2015	no	18,197	6pm-7pm
6/25/2015	yes	18,114	4pm-5pm
9/11/2015	yes	18,019	4pm-5pm
6/26/2015	yes	17,950	4pm-5pm
9/8/2015	no	17,875	4pm-5pm
7/30/2015	yes	17,750	4pm-5pm
7/1/2015	yes	17,734	2pm-3pm
8/18/2015	yes	17,372	4pm-5pm
6/12/2015	yes	17,275	5pm-6pm

Note. — This table reports the days with the top 20 peak loads for PG&E in the summer of 2015. Column 2 indicates whether an event day was called on that day. Column 3 reports the PG&E maximum load, which is the highest five-minute real-time demand at the NP15 aggregation node reported by the California Independent System Operator (CAISO) at oasis.caiso.com. The hour of maximum load signifies the hour of the day in which the maximum load occurred.

Appendix Table A6: The Effect of Peak Pricing on Peak Electricity Consumption: Establishment Classification Robust

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV FE	IV RD	IV FE	IV RD	IV FE	IV RD
Peak pricing	−0.0545	−0.2284	0.0347	−0.0039	−0.1434***	−0.3479**
	(0.0437)	(0.2379)	(0.0711)	(0.4764)	(0.0512)	(0.1677)
Establishments	6,247	6,247	4,330	4,330	1,917	1,917
Event day kWh usage	5.47	5.47	4.92	4.92	6.73	6.73
Average temperature	77	77	71	71	92	92

Note. — This table reports regression coefficients from six separate 2SLS regressions where ambiguously classified establishments are dropped. The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator of enrollment in peak pricing, for which I instrument with eligibility status. The coefficients show the impact of peak pricing on peak consumption between 2:00 pm and 6:00 pm. Appendix Section B.2 outlines the establishment classification process and which establishments are dropped for this specification. The results show similar responses to the primary specification shown in Table 3 and the RD results show in Table A9. "IV" and "RD" correspond to the instrumental variables and regression discontinuity approaches estimated using Equations (1) and (A1). All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors are two-way clustered at the establishment and hour-of-sample levels. RD errors are clustered at the distance from threshold level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A7: Impact of Time of Use Pricing on Peak Consumption when First Implemented

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	All days	Event days	All days	Event days	All days	Event days
TOU	0.0363	0.0383	0.0343	0.0235	0.0390	0.0478
	(0.0296)	(0.0464)	(0.0538)	(0.0830)	(0.0327)	(0.0532)
Establishments	7,383	7,383	5,059	5,059	2,324	2,324
Event day kWh usage	4.99	5.45	4.75	4.96	5.52	6.52
Average temperature	71	76	66	69	79	90

Note. — This table reports regression coefficients from six separate 2SLS regressions. The dependent variable in all regressions is the log of establishment hourly kWh consumption. I use the same IV identification strategy from Section 4.2 that is used to identify peak pricing impacts in 2015. Establishments that are eligible for peak pricing in 2015 are the same that are eligible for TOU in 2013. TOU is an indicator for being on Time of Use (TOU) pricing in the summer of 2013, for which I instrument with eligibility status. See Appendix Section C for more details. The coefficients show the impact of TOU pricing on consumption between 2:00 pm and 6:00 pm in the summer of 2013. The regression is estimated for just the event days and for all summer days in 2012 and 2013. The results show that TOU pricing did not have a significant impact on peak consumption for any group. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors are two-way clustered at the establishment and hour-of-sample levels. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A8: The Effect of Peak Pricing Eligibility on Enrollment (First Stage): Regression Discontinuity Approach

	(1) All PG&E	(2) Coastal	(3) Inland
Eligible × Post	0.0932**	0.0538	0.2258***
	(0.0359)	(0.0361)	(0.0449)
Establishments	7,435	5,096	2,339
F statistic	24	15	45

Note. — This table reports regression coefficients from three separate first-stage regressions estimated using the RD approach in Equation (A2). The dependent variable in all regressions is a binary indicator if an establishment is enrolled in the peak pricing program. Eligible × Post is an interaction of an establishment's eligibility for peak pricing and 2015. The coefficients show the impact of peak pricing eligibility on program enrollment. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. RD errors are clustered at the distance from threshold level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A9: The Effect of Peak Pricing on Peak Electricity Consumption: Regression Discontinuity Approach

	(1) All PG&E	(2) Coastal	(3) Inland
Peak pricing	−0.21519	−0.05837	−0.28278**
	(0.21019)	(0.42267)	(0.13790)
Temperature	−0.00846***	−0.01675***	0.02842***
	(0.00313)	(0.00621)	(0.00780)
Temperature squared	0.00010***	0.00015***	−0.00010**
	(0.00002)	(0.00004)	(0.00004)
Establishments	7,435	5,096	2,339
Event day kWh usage	5.55	5.03	6.70
Average temperature	78	71	92

Note. — This table reports regression coefficients from three separate 2SLS regressions estimated using Equation (A1). The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator for enrollment in peak pricing, for which I instrument with eligibility status. The coefficients show the impact of peak pricing on peak consumption between 2:00 pm and 6:00 pm. For inland establishments, the coefficient corresponds to a 13.5 percent reduction in usage. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. RD errors are clustered at the distance from threshold level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A10: The Effect of Peak Pricing on Peak Electricity Consumption: Intent to Treat

	(1) All PG&E	(2) Coastal	(3) Inland
Peak pricing	−0.01549*	0.00130	−0.05267***
	(0.00920)	(0.01095)	(0.01656)
Temperature	−0.00486**	−0.01763***	0.02310***
	(0.00238)	(0.00367)	(0.00663)
Temperature squared	0.00008***	0.00015***	−0.00007*
	(0.00001)	(0.00002)	(0.00004)
Establishments	7,435	5,096	2,339
Event day kWh usage	5.55	5.03	6.70
Average temperature	78	71	92

Note. — This table reports regression coefficients from three separate regressions estimated using Equation (1) where $\widehat{Peak}_{it}$ is replaced with the eligibility indicator $Eligible_i t$. The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator for enrollment in peak pricing, for which I instrument with eligibility status. The coefficients show the impact of peak pricing on peak consumption between 2:00 pm and 6:00 pm. For inland establishments, the coefficient corresponds to a 13.5 percent reduction in usage. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors are two-way clustered at the establishment and hour-of-sample levels. RD errors are clustered at the distance from threshold level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A11: OLS Impact of Peak pricing on Peak Electricity Consumption

	(1) All PG&E	(2) Coastal	(3) Inland
Peak pricing	−0.0469***	−0.0272	−0.0589**
	(0.0149)	(0.0176)	(0.0244)
Establishments	7,435	5,096	2,339
Event day kWh usage	5.59	5.03	6.70
Average temperature	78	71	92

Note. — This table reports regression coefficients from three separate OLS regressions. The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator for enrollment in peak pricing. This specification uses the 13 percent of establishments on peak pricing as the treatment group and the 87 percent not on peak pricing as the control group. The coefficients show the OLS estimated impact of peak pricing on consumption between 2:00 pm and 6:00 pm. The results show smaller impacts from peak pricing than the primary specification instrumented version shown in Table 3. The smaller impacts suggest that the control group is decreasing its usage over time, resulting in a downward-biased treatment effect. The errors are two-way clustered at the establishment and hour-of-sample levels. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Errors are two-way clustered at the establishment and hour-of-sample levels.

Appendix Table A12: The Effect of Peak Pricing on Peak Electricity Consumption: Weather Station Clustering Robust

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	RD	IV	RD	IV	RD
Peak pricing	−0.0697*	−0.2152	0.0084	−0.0584	−0.1451***	−0.2828**
	(0.0403)	(0.2046)	(0.0729)	(0.4070)	(0.0441)	(0.1274)
Establishments	7,435	7,435	5,096	5,096	2,339	2,339
Event day kWh usage	5.55	5.55	5.03	5.03	6.70	6.70
Average temperature	78	78	71	71	92	92

Note. — This table reports regression coefficients from six separate 2SLS regressions. The IV regressions are the same as the primary specification shown in Table 3, but with errors clustered at the weather station level. I use weather data from Mesowest, which has 297 weather stations that provide hourly data. "IV" and "RD" correspond to the instrumental variables and regression discontinuity approaches estimated using Equations (1) and (A1). For the IV regressions, errors are two-way clustered at the weather station and hour-of-sample. For the RD regressions, errors are two-way clustered at the weather station and distance from threshold. The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator of enrollment in peak pricing, for which I instrument with eligibility status. The coefficients show the impact of peak pricing on peak consumption between 2:00 pm and 6:00 pm. All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects.

Appendix Table A13: Robustness: Opt-in Peak Pricing Establishments Included

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV FE	IV RD	IV FE	IV RD	IV FE	IV RD
Peak pricing	−0.0615	−0.1493	0.0145	0.1177	−0.1375***	−0.2765*
	(0.0431)	(0.1958)	(0.0726)	(0.4408)	(0.0480)	(0.1466)
Establishments	7,669	7,669	5,272	5,272	2,397	2,397
Event day kWh usage	5.54	5.54	5.02	5.02	6.71	6.71
Average temperature	78	78	71	71	92	92

Note. — This table reports regression coefficients from six separate 2SLS regressions. The results reflect the primary specification shown in Table 3 with the 234 establishments that voluntarily opted into peak pricing included. See Appendix Section D.4 for more details. Including these establishments does not significantly impact the results. The dependent variable in all regressions is the log of establishment hourly kWh consumption. Peak pricing is an indicator of enrollment in peak pricing, for which I instrument with eligibility status. The coefficients show the impact of peak pricing on peak consumption between 2:00 pm and 6:00 pm. "IV" and "RD" correspond to the instrumental variables and regression discontinuity approaches estimated using Equations (1) and (A1). All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors are two-way clustered at the establishment and hour-of-sample levels. RD errors are clustered at the distance from threshold level. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Appendix Table A14: Welfare Impacts of Peak Pricing Under Alternate Scenarios with Temperature Response from 102 to 104 Day Ahead Max Temperature Forecast Days

Scenario	(1) $.85/kWh peak (current price)	(2) $1.35/kWh peak (large C&I peak price)	(3) $1.85/kWh peak (high price)
Panel A: Linear demand			
15 days/summer	$199	$265	$264
101 degree trigger (8 days)	$236	$372	$451
Super-peak days (3 days)	$263	$448	$585
Panel B: Constant elasticity demand			
15 days/summer	$237	$265	$265
101 degree trigger (8 days)	$268	$323	$344
Super-peak days (3 days)	$291	$365	$401

Note. — This table shows the welfare benefits (in millions of 2016 dollars) of the peak pricing program under different program design scenarios where the savings come from inland establishments in Table 5 on days with a day-ahead forecast of 102 to 104 degrees. Panel A shows the welfare calculations using a linear demand curve and Panel B does the same using a constant elasticity demand curve. Column (1) shows outcomes under the current $.85/kWh peak price. Column (2) shows the estimated outcomes if the peak price were set at $1.35, which is the level of large commercial and industrial customers and is based on a PG&E valuation of capacity at peak. Column (3) shows the impacts if the price was set at $1.85/kWh. The first row of each panel reflects the current 15 event days per summer and the entry in the top left shows the welfare impacts estimated for the current program. The middle row of each panel reflects the proposed alternate 101 degree trigger for event days, and the bottom row of each panel shows the hypothetical scenario when only the three super-peak event days each year could be called. The welfare calculations assume that peak wholesale prices are greater than or equal to the peak price in each column.

Appendix Table A15: Welfare Impacts of Peak Pricing Under Alternate Scenarios with Double the Demand Response

Scenario	(1) $.85/kWh peak (current price)	(2) $1.35/kWh peak (large C&I peak price)	(3) $1.85/kWh peak (high price)
Panel A: Linear demand			
15 days/summer	$319	$425	$424
101 degree trigger (8 days)	$378	$595	$723
Super-peak days (3 days)	$421	$717	$937
Panel B: Constant elasticity demand			
15 days/summer	$468	$573	$614
101 degree trigger (8 days)	$512	$647	$711
Super-peak days (3 days)	$543	$700	$781

Note. — This table shows the welfare benefits (in millions of 2016 dollars) of the peak pricing program under different program design scenarios. In this table I assume establishment response is double the main specification in Table 3. Panel A shows the welfare calculations using a linear demand curve and Panel B does the same using a constant elasticity demand curve. Column (1) shows outcomes under the current $.85/kWh peak price. Column (2) shows the estimated outcomes if the peak price were set at $1.35, which is the level of large commercial and industrial customers and is based on a PG&E valuation of capacity at peak. Column (3) shows the impacts if the price was set at $1.85/kWh. The first row of each panel reflects the current 15 event days per summer and the entry in the top left shows the welfare impacts estimated for the current program. The middle row of each panel reflects the proposed alternate 101 degree trigger for event days, and the bottom row of each panel shows the hypothetical scenario when only the three super-peak event days each year could be called. The welfare calculations assume that peak wholesale prices are greater than or equal to the peak price in each column.

Appendix Table A16: Welfare Impacts of Peak Pricing Compared to First-Best Real-Time Price

Event days called per summer	(1) $.85/kWh peak price (peak price < RTP)	(2) $1.35/kWh peak price (peak price = RTP)	(3) $1.85/kWh peak price (peak price > RTP)
8 event days (well targeted)	51%	**87%**	73%
15 event days (current)	**45%**	69%	35%

Note. — This table compares the peak pricing program to the first-best, real-time price across a number of scenarios. The percent values reflect the percent of the welfare benefits that the peak pricing scenario can achieve compared to the first-best alternative. The table shows results similar to Table 11, except prices remain at the high $1.35/kWh level for four hours between 2:00 pm and 6:00 pm instead of for just one hour. Column (1) reflects the current program, where peak prices are set at $.85/kWh, which is below the optimal level. Column (3) shows the impacts when prices are set above this level. The top row reflects the outcomes when eight event days are called per year. The bottom row shows the results for the current program, in which I assume 15 event days are used each summer.

Appendix Table A17: Welfare Impacts of Peak Pricing Compared to First-Best, Real-Time Price: Constant Elasticity Demand Curve

Event days called per summer	(1) \$.85/kWh peak price (peak price < RTP)	(2) \$1.35/kWh peak price (peak price = RTP)	(3) \$1.85/kWh peak price (peak price > RTP)
8 event days (well targeted)	69%	**87%**	80%
15 event days (current)	**63%**	75%	60%

Note. — This table compares the peak pricing program to the first-best, real-time price across a number of scenarios. The comparison uses a constant elasticity demand curve to estimate net consumer surplus losses and demand above the empirically observed price. The percent values reflect the percent of the welfare benefits the peak pricing scenario can achieve compared to the first-best alternative. For this table, the optimal peak price is set at \$1.35/kWh for one hour on three super-peak days per summer. Column (1) reflects the current program, where peak prices are set at \$.85/kWh, which is below the optimal level. Column (3) shows the impacts when prices are set above this level. The top row reflects the outcomes when eight event days are called per year. The bottom row shows the results for the current program, in which I assume 15 event days are used each summer. The current program achieves 44 percent of the first-best policy, while the well-targeted program could achieve 83 percent of the benefits.