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

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November 9, 2016

JOB MARKET PAPER

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Abstract

In electricity markets, the price paid by retail customers during periods of peak demand is far below the cost of supply. This leads to overconsumption during peak periods, requiring the construction of excess generation capacity compared to first-best prices that adjust at short time intervals to reflect changing marginal cost. In this paper, I investigate a second-best policy designed to address this distortion, and compare its effectiveness to the first-best. The policy allows the electricity provider to raise retail price by a set amount (usually 3 to 5 times) during the afternoon hours of a limited number of summer days (usually 9 to 15). Using a quasi-experimental research design and high-frequency electricity consumption data, I test the extent to which small commercial and industrial establishments respond to this temporary increase in retail electricity prices. I find that establishments reduce their peak usage by 13.4% during peak hours. Using a model of capacity investment decisions, these reductions yield $154 million in welfare benefits, driven largely by reduced expenditures on power plant construction. I find the current policy provides 43% of the first-best benefits but that, with improvements in targeting just the days with the highest demand, a modified peak pricing program could achieve 80% welfare gains relative to the first-best pricing policy.

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1 Introduction

Supplying electricity during periods of peak demand is expensive. Because electricity storage is not cost effective, sufficient generation capacity must exist to satisfy demand at all moments in time. To avoid blackouts, electricity providers regularly invest in power plants that operate only on the few highest demand days of the year. Electricity prices, however, do not reflect the high cost of meeting peak demand. Most retail prices reflect the average cost of providing power and do not vary based on when this power is consumed. As a result, retail electricity customers are undercharged for their electricity at peak times, leading to inefficiently high consumption (Boiteux 1949; Steiner 1957).

In the long run, higher peak consumption necessitates additional generation capacity. In most U.S. electricity markets, capacity investment decisions are made by the regulator through the "resource adequacy" process (Joskow and Tirole 2007). The regulator uses past demand levels to determine generation capacity requirements for electricity providers. If retail prices were adjusted to reflect the full cost of generation during peak periods, this would reduce both peak demand and the regulator's capacity requirement. Borenstein (2005) and Borenstein and Holland (2005) estimate the efficiency loss due to flat retail prices to be 5%-10% of wholesale electricity costs.

Inefficient peak demand pricing also occurs in other contexts. Vickrey (1963, 1969) outlines the problem of unpriced traffic congestion, where drivers do not pay the full external costs of using infrastructure at peak hours. Instead, drivers pay for the use of road networks through a flat gasoline tax, which is similar to the average pricing structure used for electricity. In the long run, this can lead to overinvestment in transportation infrastructure, as additional capacity is built to alleviate unpriced congestion instead of providing the greatest social marginal benefit.[1]

For both electricity markets and traffic congestion, the first-best policy is to charge a price that reflects the short-run marginal scarcity value during periods of peak demand. In the case of electricity, this policy is "real-time pricing" (RTP), under which the retail price changes hourly or more frequently. RTP is technologically feasible at low cost for most commercial and industrial customers due to the wide-scale deployment of smart meters. Despite its large potential benefits, however, real-time pricing remains politically infeasible. Because many customers receive large cross-subsidies under existing flat pricing schemes, mandatory real-time pricing would be difficult to implement without politically unpopular transfer payments (Borenstein 2007b).

[1] A related problem is seen in the provision of public transportation, where fares typically do not vary over time to reflect the marginal costs (Mohring 1972; Parry and Small 2009).

The inability to implement real-time pricing suggests two important questions. First, how large are the potential benefits of real-time pricing? This depends on the extent to which customers would respond to short-run price changes. If demand is sufficiently price inelastic, then any potential costs of implementing real-time pricing could outweigh the benefits. Borenstein (2005), however, shows that, for most plausible elasticities, the benefits are very likely to outweigh the costs. Second, to what extent can second-best policies achieve the benefits of real-time pricing? This paper addresses the second question by examining a common second-best policy that raises electricity prices on high demand days, and by measuring this program's effectiveness compared to the first-best, real-time pricing policy.

I study the largest peak demand program to date in the U.S., which includes commercial and industrial (C&I) establishments in the Pacific Gas & Electric (PG&E) Northern California service territory. Programs like PG&E's "Peak Pricing" are among the most common time-varying pricing policies in the U.S. The popularity of such programs has grown with the recent deployment of advanced smart meter technology. The peak pricing implementation I study gives PG&E the ability to declare up to 15 "event days" per summer, during which the retail electricity price more than triples between 2:00 pm and 6:00 pm. Customers are notified one day before each event day, and they receive a small discount on all other summer consumption in exchange for their participation in the program. My analysis focuses on small commercial and industrial (C&I) establishments because the way in which the program was implemented for these customers created a quite similar, and exogenous, control group to which the treated group could be compared.

To identify the impacts of this peak pricing program, I leverage the rules that governed its rollout. Establishments were placed on peak pricing by default only after they satisfied a set of eligibility criteria. They were then allowed to opt out. I compare establishments that satisfied the eligibility criteria for the first wave of peak pricing to similar establishments that just missed being eligible by not satisfying the eligibility criteria. I provide supporting evidence that assignment to peak pricing is as-good-as-random, using data from before program implementation. I use both a panel fixed effects instrumental variables strategy and a regression discontinuity design to identify program impacts.

Using hourly electricity consumption data, I find that peak pricing reduces electricity consumption for non-coastal establishments by 13.4% on event days, compared to a control group. I estimate that the program will reduce PG&E peak demand by 118 MW among small C&I customers when fully implemented by the summer of 2018, thereby reducing the need for one or more specialized power plants that are constructed with the sole purpose of generating electricity during the highest demand hours of the year. To evaluate the welfare impacts of peak pricing, I model the regulatory resource adequacy process that governs the amount of capacity that is built specifically to meet peak demand. I find that the estimated reduction in peak demand increases welfare on the PG&E grid by $154 million over a 30-year period, due to avoided generation capacity investments.

To put these welfare effects in perspective, I compare my estimated peak demand reductions to a first-best real-time price. Using the empirical estimates of demand response, I calculate that the current program recovers 43% of the first-best welfare gains. I then consider simple adjustments to the policy to better target the highest demand days, and show that substantial welfare gains would likely result from reducing the number of event days and increasing the event day price. This better-targeted peak pricing policy could achieve 80% of first-best welfare gains.

The importance of the design of second-best policies has also been found in other contexts. Ito and Sallee (2014) and Sallee and Slemrod (2012) show that notched levels of fuel economy regulation can lead car makers to strategically manipulate their production decisions for favorable treatment. This behavior can lead to negative welfare outcomes compared to a differently designed, smooth fuel economy regulation. Ramnath (2013) finds that the design of the Saver's Credit in the U.S. tax code distorts household income reporting behavior in a way that is potentially costly to the program.

This paper makes three distinct contributions to the economics literature. First, no previous academic research has estimated the impacts of peak pricing on the commercial and industrial sector, which is responsible for two-thirds of California and U.S. electricity demand (Energy Information Administration 2016). The program rollout that I study caused more business establishments to move to peak pricing than any similar program in the U.S. Previous empirical work has focused on peak pricing programs in the residential sector (Bollinger and Hartmann 2015; Fowlie et al. 2015; Ito et al. 2015; Jessoe and Rapson 2014; Wolak 2007, 2010).

The paper also contributes to the literature on long-run investment efficiency in electricity markets. This literature typically relies on simulation and stylized models of power plant capacity construction to value the impacts of alternate pricing policies (Borenstein 2005, 2012; Borenstein and Holland 2005; Holland and Mansur 2006). I depart from this approach, and instead focus on the mechanisms that actually drive power plant construction in a regulatory setting. Using this technique, I am able to estimate welfare impacts under a more realistic set of assumptions.[2] I am also able to evaluate which program design features specifically drive impacts, allowing me to propose improvements informed by the empirical estimates.

[2]My approach complements the work of Boomhower and Davis (2016), who use capacity market payments to value the benefits of energy efficiency at peak hours.

Finally, the paper contributes to the literature on second-best pricing policies under capacity constraints. The existing literature is mainly theoretical in nature, applying a range of assumed parameter values to stylized models. For example, Arnott et al. (1993) use numerical examples to estimate Vickrey's (1969) model of traffic congestion and simulate outcomes under different pricing regimes. Similarly, research on airplane landing congestion relies on stylized numerical examples to analyze optimal pricing (Brueckner 2002, 2005, 2009). My paper contributes to this literature by estimating the causal effects of a peak pricing program focused on capacity constraints. My empirical estimates enter directly into the welfare calculations, while allowing evaluation of potential improvements to program design.

The rest of the paper is organized as follows: Section 2 discusses the electricity industry, related literature, and the peak pricing program in detail. Section 3 outlines the data used in the analysis. Section 4 describes the empirical strategy and Section 5 presents results. Section 6 proposes a model for calculating the welfare impacts of peak pricing programs, discusses potential improvements, and benchmarks the outcomes to the first-best, real-time price. Section 7 concludes.

2 Background

Most electricity in the U.S. is sold to retail customers at a constant flat rate that does not reflect the time-varying marginal cost of producing another kilowatt-hour (kWh). In most cases, the marginal cost consists of two components. The first is the short-run marginal production cost (SRMC), which includes the fuel costs associated with producing an additional kWh. The second is due to a regulatory process in most states that requires an electricity supplier to demonstrate it controls adequate capacity to meet the peak demand it serves. These "resource adequacy" requirements are generally based on previous peak demand quantities. As a result, each additional kWh consumed on the highest demand days of the year increases future capacity requirements, adding significant costs.

The welfare costs of the current system of flat-rate pricing are well studied in the economics literature (Borenstein 2005, 2012; Borenstein and Holland 2005). An efficient alternative to the current system is to vary the retail price of electricity to reflect the time-varying marginal cost of supply. This could be done by passing through the wholesale electricity market prices to retail customers in real time. Real-time pricing is technically feasible at low cost due to the wide-scale deployment of smart meters over the last decade

(Joskow and Wolfram 2012).[3] Existing research shows that RTP could provide large, long-run efficiency gains compared to the current flat-rate pricing by reducing total quantity demanded (load) during high demand hours and increasing load when generation costs are low (Holland and Mansur 2006). By reducing peak demand, RTP reduces the need for costly power plants specifically built for the hottest few days of the year.

Despite the large potential welfare gains from RTP, implementation is politically challenging. Retail electricity prices are set through a regulatory process under political constraints. Some customers would face significantly higher energy bills under real-time pricing, creating a constituency opposed to the new pricing system. Borenstein (2007b) shows that substantial transfers would be required to keep many customers whole when transitioning to a real-time price. Other customers are wary of the potential volatility in electricity bills that could result from real-time pricing. Borenstein (2007a) shows that switching to a real-time price could increase the month-to-month bill volatility for commercial and industrial customers by a factor of two to four, but that simple hedging programs offered by the utility could reduce most of the variation.

In the absence of RTP, policymakers have introduced a number of other policies that pass through some portion of time-varying prices to customers without unexpected volatility. Time of Use (TOU) pricing adjusts the price of electricity in a prescribed manner by hour, day and season, but does not pass through high price events. For example, a previously flat retail price of \$.20/kWh could be changed to a TOU rate of \$.25/kWh between noon and 6:00 pm, when demand is generally high, and \$.15/kWh at night. These prices can capture some of the average shape of marginal costs, but they do not adjust when wholesale costs spike on the highest demand days of the year. Borenstein (2005) shows that TOU captures only a small amount of the efficiency gains of RTP.

Peak pricing programs, like the one studied in this paper, are designed to address the costs associated with the highest demand days of the year. To date, however, research on consumer response to peak pricing programs has focused on the residential sector. Existing studies find that households reduce their energy consumption when facing high prices during peak hours, though the estimated response magnitude varies across studies and depending on the use of automation technology. There has been no published research to date on peak pricing in the commercial and industrial sector. Because firms are responsible for twice the electricity usage of the residential sector, this is an important gap.

[3]Smart meter deployment is financially justified because the meters eliminate the need to pay employees to manually check electricity usage every month. As of 2014, the smart meter penetration for C&I customers in California and the rest of the US was 89% and 66% respectively (Energy Information Administration 2014).

The existing residential peak pricing studies have been run as utility experiments and pilot programs. Fowlie et al. (2015) partnered with the Sacramento Municipal Utility District in California to study the impacts of opt-in versus opt-out peak pricing programs. They find that households in the opt-out program reduce their electricity usage by 13.9% during peak pricing events. Households that chose to opt-in to peak pricing reduced their usage by 27.3%. Other residential peak pricing research has focused on the importance of information and technology in responding to peak pricing. Jessoe and Rapson (2014) find that providing households with detailed usage data results in substantially larger reductions than just the price alone. Bollinger and Hartmann (2015) investigate how automation technology that adjusts consumption in response to higher prices affects the response to peak pricing. They find that households are more than twice as responsive when they are given automation technology and higher prices along with price information, compared with price information alone. My paper is the first to investigate whether a similar overall response to peak prices is also found among commercial and industrial customers.

2.1 PG&E's Peak Pricing Program

The PG&E peak pricing program for small C&I customers raises the price of electricity from the normal price of \$.25/kWh to \$.85/kWh from 2:00 pm to 6:00 pm on 9 to 15 "event days" per year. The program runs between June 1st and October 31st each year. Enrolled establishments receive a discount of \$.01/kWh on all other consumption during the summer to compensate them for participating. PG&E determines when event days are called based on day-ahead weather forecasts.[4] Establishments are notified by 2:00 pm the day before an event via e-mail, text message and/or phone call. Establishments are told about Monday event days on the prior Friday.

Establishments are given "bill protection" for the first summer they are enrolled. This protection guarantees that customers do not pay more in their first summer as a consequence of the peak pricing rates. If their total utility bill is higher between June 1 and October 31 on peak pricing than it would have been if they had opted out, the customer is refunded the difference. Establishments were sent a letter by PG&E in November 2015 informing of them of how much money they saved or would have lost during the first year of the program. The letter explained that the bill protection credit would be dispersed on their November 2015 bill, and that they would no longer receive bill protection going forward. In Section 5, I discuss the potential impact of bill protection on the estimates of price response.

[4]When the forecasted maximum temperature at a set of five specified weather stations exceeds a given "trigger" temperature, an event day is called. See Appendix Section A for specific details on this process.

The enrollment data suggests that customers will remain in the peak pricing program after they no longer have bill protection. In the first summer of peak pricing, 89% of establishments in my sample would have lost money if not for bill protection. The average loss for these establishments was $104 over the summer of 2015.[5] Despite these losses, only an additional 5.5% of establishments dropped out between their bill protection payment in November 2015 and the most recent data from October 2016. This suggests that, even after the first summer, when establishments no longer have bill protection, they do not choose to leave the peak pricing program.

I study the first wave of enrollments, in which 29% of small C&I accounts were placed on peak pricing and given the ability to opt out at any time using a simple web interface.[6] Only 5.9% of the establishments in the first wave opted out before the first summer. An additional 5.3% of establishments dropped out during the first summer of the program. The high number of people remaining in the program reflects both the role of default bias and the impact of bill protection. There is a large economics literature documenting the impact that changing the default can have on choice, including Abadie and Gay (2006), Choi et al. (2004), Johnson et al. (2002), and Madrian and Shea (2001), among many others.

3 Data

I use confidential data provided by PG&E for this analysis. The data consist of hourly electricity usage data for 19,071 establishments for the summers of 2014 and 2015. These establishments are used in the analysis because their smart meter data started within 6 months of September 1, 2011, which is a key feature of the identification strategy and is described in the following section. I classify establishments in the sample as being in coastal or inland areas based on a PG&E designation. This classification is used frequently in my analysis of peak pricing because the two regions have vastly different climates. The coastal region, which runs the length of the coast in PG&E's service territory, has much milder summers compared to the inland region.[7]

To construct the final dataset, I combine hourly usage data with establishment characteristics. Exact establishment latitude and longitude coordinates were provided by PG&E,

[5] 2015 was the first year that small C&I establishments were included in peak pricing. The program is designed to be revenue neutral with respect to enrollees, suggesting that the $.01/kWh subsidy for non-event hours may need to be increased in future years.

[6] See Appendix Figure A1 for an example of the letter sent to establishments 30 days before the program started, with directions on how to opt out.

[7] Appendix B describes the creation of the dataset in detail. See Appendix Figure A2 for a map of the 7,435 establishments used in the primary specification and their region designation.

and are used to match establishments to hourly weather data obtained from Mesowest.[8] I observe when a customer was placed on the opt-out tariff and whether they decided to opt out. I also observe industry classification in the form of North American Industry Classification System (NAICS) codes for 89.2% of establishments in the sample.

PG&E categorizes its C&I customers based on electricity consumption. This paper focuses on the smallest non-residential PG&E rate, the A-1 tariff, because the peak pricing rollout for this group allows me to causally identify program impacts.[9] I remove smaller individual meters that consumed below 800 kWH/month in the summer of 2014.[10] This leaves me with the 19,071 establishments used in the analysis. The average customer in the sample consumed 87 kWh/day and spent $560/month on electricity in the summer of 2014. This is a larger amount than the average residential household, which consumed 21 kWh/day. Figure 1 shows the average summertime hourly consumption profile of the establishments in the sample, where the vertical lines indicate the peak pricing window.

There are approximately 283,000 C&I customers of this size profile in the PG&E service territory. These establishments make up 82% of the load of the small C&I class. In total, small C&I customers constitute about 2,000 MW of peak load, which is around one-tenth of PG&E's total peak load. The customers in my sample are typically smaller businesses for which energy is not a major input, including restaurants, barber shops, bakeries, corner stores, small retail shops, strip mall storefronts, law offices and doctors' offices. Energy intensive establishments from industries such as food processing, cement manufacturing, aluminum smelting or commercial establishments with large refrigeration needs are on different tariffs and are not studied because they face different electricity prices and event day prices.[11]

[8]The hourly weather station data were cleaned to remove any weather stations with unreliable data and are matched to the closest establishment. The final dataset contained measurements from 297 weather stations over 2014 and 2015.

[9]Establishments are placed on the A-1 tariff if they consume less than 150,000 kWh/year and if they have peak usage of less than 75 kW. The average PG&E residential customer consumes around 8,000 kWh/year. PG&E, like most utilities, imposes a demand charge for its larger non-residential customers. This charge is based on the customer's maximum flow of electricity in a given month. A-1 establishments do not pay a demand charge.

[10]I drop low-usage meters because most are not associated with an establishment. For example, a single meter may be attached to a sign in a strip mall, but may not be associated with other uses of the business. A full accounting of how the final dataset was constructed and cleaned is provided in Appendix Section B.

[11]Most larger establishments were moved to peak prices using different criteria before 2015. As a result of how this was done, there is no way to reliably identify the impacts of peak pricing on their usage.

4 Empirical Strategy

4.1 Natural Experiment in Peak Pricing Enrollment

The nature of the PG&E peak pricing program does not permit the use of an OLS selection-on-observables design to carry out a simple comparison between enrolled customers and those yet to be enrolled. That approach would likely result in a comparison between dissimilar establishments and therefore biased estimates of program impacts. To avoid potential bias, I use an instrument that leverages a natural experiment in the rollout of opt-out peak pricing for the summer of 2015.

PG&E used a set of rules to determine when an establishment would be placed on opt-out peak pricing. They evaluated their customer base once per year starting in November 2014 to determine which establishments were eligible. This paper examines the first wave of this rollout. The regulator required that an establishment had a history of high-frequency metering data before they were placed on peak pricing, so that customers could be informed about the potential price impacts and could make informed decisions.

Specifically, *establishments' smart meter data needed to have started before September 1, 2011 to be eligible for the 2015 rollover to opt-out peak pricing.* Figure 2 provides a timeline of this process. I classify establishments in two groups: those that were eligible for peak pricing in 2015 and those that were not. Those establishments with high-frequency data starting after September 1, 2011 were deemed ineligible for peak pricing in 2015.

The impacts of this eligibility status can be seen more than three years after the September 1, 2011 threshold, when treatment started.[12] In November, 2014, a portion of the eligible establishments were moved to opt-out peak pricing.[13] In contrast, none of the ineligible establishments were moved and will have to wait for subsequent rollovers.

To illustrate the transition to peak pricing, Figure 3 breaks down the eligible and ineligible groups by the week their smart meter data were first collected. The horizontal axis shows weeks relative to the September 1, 2011 cutoff. The vertical axis displays the percent of each bin that was placed on opt-out peak pricing for the summer of 2015. A portion of the establishments to the left of the September 1, 2011 threshold were moved to peak pricing, while no establishments to the right were moved.

The date an establishment's smart meter data began is based on when its smart meter was installed. PG&E started installing smart meters in 2008, long before planning began for

[12] The long time lag was due to a number of requirements that the regulator had given PG&E about the information that had to be available to an establishment before it was transitioned to opt-out peak pricing. See Appendix Section C for more details on these requirements.

[13] Which establishments were moved depends on technological factors, which are described later in this section.

the peak pricing program rollout. PG&E treated installations as general capital upgrades, with installation decisions based on factors such as labor availability and logistical constraints. Installations typically took 5-15 minutes, and did not require the account holder to be present. The smart meter installation date was not related to consumption or to any observable characteristics of a given establishment.[14]

The nature of the smart meter rollout suggests that establishments on either side of the September 1, 2011 threshold are similar. The peak pricing eligibility cutoff was not known when the smart meters were installed, suggesting that establishments had no reason to strategically adjust their installation date. While the installations are as good as random over short periods of time, there are longer-term patterns to consider. Smart meters were installed across California during this time period, but certain areas of the state were emphasized earlier in the rollout compared to others. I select customers within an eight-week bandwidth of the September 1, 2011 threshold to avoid potential bias from long-term installation trends. This bandwidth is indicated as the dashed vertical lines in Figure 3, and cuts the sample to 7,435 establishments.[15] Table 1 shows the summary statistics for a number of characteristics broken out by peak pricing eligibility. The table shows that establishments within eight weeks of the September 1, 2011 cutoff are observationally similar to each other.

One noteworthy feature of the September 1, 2011 cutoff is that eligible establishments closer to the threshold were less likely to be rolled over. This pattern is due to technical requirements that govern when high-frequency usage data is considered usable. PG&E requires that the "remote meter reads become stable and reliable for billing purposes" before they can be used for any official purpose (Pacific Gas & Electric 2010).[16] The validation process can be quick for some establishments, but can take a number of months to complete for others.[17] For this reason, establishments that had high-frequency data for longer (farther to the left in Figure 3) are more likely to be placed on opt-out peak pricing in the summer of 2015. The eligible establishments that missed peak pricing in the summer of 2015 due to technical requirements were scheduled to be moved over for the summer of 2016.

I use two different identification strategies to estimate program impacts. I first instrument for program participation based on the high-frequency meter data start date eligibility criterion. Second, I use a regression discontinuity approach around the September 1, 2011 threshold. This explicitly controls for an establishment's distance in days from the September

[14]See Appendix Section C.1 for more details on the smart meter rollout, including quotes from annual reports describing the process.

[15]I consider alternate bandwidths in the results section as robustness checks.

[16]PG&E still sends employees to physically read the meters monthly until this validation is complete. See Appendix Section C.1 for more details on the validation process.

[17]Establishments to the right of the cutoff are assumed to have a similar pattern of data validation characteristics.

1, 2011 discontinuity in the post period, by using a trend line. Both approaches use establishment fixed effects to control for time-invariant characteristics. The unit of observation is the establishment-hour. In most specifications, I limit the sample to 2:00 pm-6:00 pm on event days in the summer of 2014 and 2015. In the summer of 2014, event days were called by PG&E, but they did not apply to this customer class. This makes them an ideal set of pre-period control days that are similar to the 2015 event days.

4.2 Instrumental Variables Approach

To identify peak pricing program impacts in the instrumental variables (IV) approach, I instrument for peak pricing participation with whether an establishment's smart meter was installed before September 1, 2011, limiting my sample to establishments getting smart meters within eight weeks. I estimate the impact of peak pricing using the following two equations via 2SLS:

$$Q_{it} = \beta_1 \widehat{Peak}_{it} + \beta_2 Temp_{it} + \beta_3 Temp_{it}^2 + \zeta_t + \gamma_{ihd} + \epsilon_{it} \tag{1}$$

$$Peak_{it} = \alpha_1 \{Eligible \times Post\}_{it} + \alpha_2 Temp_{it} + \alpha_3 Temp_{it}^2 + \zeta_t + \gamma_{ihd} + \eta_{it} \tag{2}$$

Equation (1) is the second stage. $\widehat{Peak}_{it}$ is an indicator of peak pricing enrollment for establishment i in hour-of-sample t, which is predicted in the first stage regression (Equation 2) using the eligibility instrument interacted with the 2015 dummy ($\{Eligible \times Post\}_{it}$).

Q_{it} is the log of electricity consumption for establishment i in hour-of-sample t. Hourly temperature is controlled for with $Temp_{it}$ and $Temp_{it}^2$.[18] Hour-of-sample fixed effects, which control for any contemporaneous shocks that affect all establishments, are captured with ζ_t. γ_{ihd} is a set of establishment fixed effects that control for time-invariant factors. Each establishment has a separate establishment fixed effect for each hour of day (h) and day of week (d) combination because these are both significant dimensions across which establishments change their energy consumption. β_1 is the coefficient of interest and represents the average hourly reduction across peak event hours in 2015. The identifying variation comes from within-establishment variation in peak electricity consumption following the implementation of the peak pricing program in 2015.

[18]The temperature controls are used to increase precision, but the results are robust to their omission.

ϵ_{it} is the error term in the second stage and η_{it} is the error term from the first stage. The panel nature of this analysis makes each of the errors potentially correlated both over time and across establishments. To account for this two-way errors dependence, I two-way cluster at the establishment and hour-of-sample level, as suggested by Cameron et al. (2011). As a result, the errors are robust to both within-establishment and within-hour-of-sample correlation.

The identifying assumption underlying the 2SLS estimation is that peak pricing eligibility is not correlated with peak electricity consumption, conditional on fixed effects and temperature controls, through any other mechanism than being placed on opt-out peak pricing. Formally, this is written as $\text{cov}(\textit{Peak Eligibility}_{it}, \epsilon_{it} \mid X_{it}) = 0$, where X_{it} represents the covariates and fixed effects that are controlled for in Equation (1). The exclusion restriction could be violated if there are time-varying trends that differentially affect establishments in the two eligibility groups. The estimation also requires a valid first stage, for which I provide evidence in Section 5.1.

Evidence of the validity of the research design restriction is provided in Figure 4, which shows the average summer 2014 (pre-period) consumption by eligibility group, after controlling for establishment-level fixed effects. The consumption patterns are similar, indicating that the eligible and ineligible establishments function as good comparison groups. Table 1 shows summary statistics by eligibility group for establishments in the eight-week bandwidth on either side of the September 1, 2011 threshold. I cannot reject that eligible and ineligible establishments are statistically the same across all observables.

4.3 Regression Discontinuity Approach

This section introduces a 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:

$$\begin{aligned} Q_{it} = \beta_1 \widehat{Peak}_{it} + \beta_2 X_i Post_t + \beta_3 X_i \{Eligible \times Post\}_{it} + \beta_7 Temp_{it} + \\ \beta_8 Temp_{it}^2 + \zeta_t + \gamma_i + \epsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} Peak_{it} = \alpha_1 \{Eligible \times Post\}_{it} + \alpha_2 X_i Post_t + \alpha_3 X_i \{Eligible \times Post\}_{it} + \\ \alpha_4 Temp_{it} + \alpha_5 Temp_{it}^2 + \zeta_t + \gamma_i + \eta_{it} \end{aligned} \tag{4}$$

Equation (3) is the second stage equation. As above, $\widehat{Peak}_{it}$ is an indicator of peak pricing enrollment for establishment i in hour-of-sample t, which is instrumented for in the first stage (Equation 4) 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 (2014). γ_i controls for establishment fixed effects.[19] 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).[20]

The main difference between the RD and IV approach is that the RD controls for the distance from the threshold in the post period. 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 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 5 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 5 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.

5 Results

5.1 Main Results

I use the IV and RD approaches to identify the impacts of peak pricing on electricity usage. Table 2 shows the first stage results from estimating Equations (2) and (4). Columns (1) and (2) show the results for the sample that spans the PG&E service territory. The first stage

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

[20] 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.

is significant for both identification strategies, and the IV approach has a larger coefficient. 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 for the IV and RD approaches are 406 and 24 respectively, providing evidence of a valid first stage. Columns (3)-(6) report the first stages for the coastal and inland regions separately. The results show a significant impact of eligibility on peak pricing enrollment for all specifications except for the coastal RD.

Table 3 shows the IV and RD impacts of peak pricing on electricity consumption. The sample for analysis comprises the 7,435 establishments with high-frequency data starting within eight weeks of the September 1, 2011 cutoff. Columns (1) and (2) show the impacts for the IV and RD strategies. Both show reductions in peak usage, but with p-values of .10 and .31 for the IV and RD approaches respectively. Columns (3)-(6) split the results by region, showing that the impact of peak prices varies substantially by geography and temperature. Coastal regions, which are characterized by lower electricity usage and temperatures, show almost no response to peak prices. In contrast, inland establishments reduce peak usage by 13.4% and 24.6% in the IV and RD approaches respectively, and both are significant at the 5% level.[21]

The results provide evidence that, in the warmer inland regions of California, peak pricing significantly impacts electricity usage. Coastal customers, however, do not seem to be as responsive. The regional nature of the results is consistent with Ito (2015), who finds that inland households are more price-elastic than coastal customers.

Figure 6 graphically shows the reduced form 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

[21] Percent reductions reflect antilog transformed coefficients. See Appendix Section D.1 for the non-instrumented OLS results, which show a smaller impact of peak pricing. Appendix Table A5 shows the results as elasticities.

to the left of the vertical line compared to the ineligible group to the right.[22] The reduced form impacts of peak pricing seen in this figure are visible but noisy, so I focus on regression analysis for the remainder of the results section.

The role of bill protection is important to consider when interpreting the results in this paper. Establishments know they cannot lose money in the first year of the program. This creates incentives similar to those in Ito (2015), where establishments, far from making money under the program, may choose to "give up," take the bill protection, and not respond to the price. The role of bill protection can be seen by examining the financial impacts of peak pricing in its first year. Only 11% of establishments in my sample saved money in the 2015 peak pricing program, with the remainder receiving the help of bill protection. As discussed in Section 2.1, only 5.5% of establishments dropped out between the time they received the bill protection credit in November 2015 and the end of the second year of the peak pricing program. The low dropout rate after most establishments would have lost money in the first year, combined with the lack of bill protection in future years, suggest that my results are a lower bound for future peak pricing impacts. If establishments are exposed to potential monetary losses, they have a larger incentive to reduce their usage. It is possible that additional establishments may opt out of peak pricing after losing money, which could reduce future aggregate impacts. However, the low observed opt-out rate after the first summer suggests that this impact may not be very large. Future years of program data are necessary to resolve the impact that opt-out behavior might have on program impacts.[23]

Both the RD and IV approaches use an eight-week bandwidth around the September 1, 2011 cutoff, but the results do not change substantially at different bandwidths, as shown in Figure 7. The results in this section are robust to a number of other specification and clustering choices, as shown in Appendix Section D.

5.2 Spillovers to Non-Event Hours

The analysis to this point has only focused on the change in usage between 2:00 pm and 6:00 pm on event days. This ignores the scope for establishments to re-optimize their usage during off-peak hours. Figure 8 shows the treatment effects for inland establishments by hour of day. The results suggest that establishments begin to reduce their energy usage around 11:00 am, with the reductions becoming statistically significant by 1:00 pm. This pattern of reductions is consistent with establishments making event day changes that spill over to

[22] 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 6.

[23] I am not able to estimate the causal impact of peak pricing without bill protection in future years because the control group used in my identifications strategy will have rolled onto peak pricing.

non-event window hours. For example, an establishment may adjust its air conditioner set point from the normal 72 degrees up to 76 degrees on event days. This behavior would reduce the overall demand for cooling on event days, leading to the reductions seen before 2:00 pm.[24] Immediately after the event window ends, usage returns to the level of the control group. Many small C&I businesses close around 6:00 pm, which might explain the return to control consumption levels.

5.3 Impacts of Temperature

The outdoor temperature on event days is much higher in the inland regions of California than on the coast.[25] This suggests that temperature could play a role in an establishment's demand elasticity. Reiss and White (2005) show that residential customers with air conditioners have more elastic demand than those without. Ideally, I would measure the impacts of peak pricing on establishments with air conditioning separately from those without, but this is not possible with the data available. Instead, I focus on the role that temperature plays in event day reductions.

Table 4 presents the results for inland establishments from interacting the treatment effect in Equations 1 and 3 with temperature.[26] The negative sign on the interaction term shows that peak reductions get larger as temperature increases. The estimated impacts are relative to a 75 degree day.[27] The IV results show a statistically significant reduction, while the RD estimates have the same sign but with a p-value of .099.

The results show that, on average, higher reductions come from higher outdoor temperatures. As a consequence, the peak pricing program may provide larger reductions on the hottest event days when the grid is most stressed. This finding is relevant to program design, because, if event days occurred only on the hottest few summer days, then reductions might be higher than the average impacts under the current program.

5.4 Firm Heterogeneity

Small C&I establishments use electricity to produce a wide range of goods and services in their day-to-day operations. For example, retail establishments have different patterns of electricity usage than office spaces or doctors' offices (Kahn et al. 2014). In this subsection, I

[24] Appendix Section A9 shows the impacts on non-event days between 2:00 pm and 6:00 pm.

[25] See Appendix Figure A4 for a map showing temperatures on event days.

[26] For the RD specification, I interact temperature with treatment and the distance from the threshold terms. The results for the coastal region remain insignificant.

[27] I re-center temperature at 75 degrees for ease of interpretation; this does not impact the peak pricing times temperature coefficient.

use the industry classification information provided by PG&E to test how different types of establishments respond to peak pricing. Specifically, I test how customer-facing and non-customer-facing establishments each respond to peak pricing. I hypothesize that customer-facing businesses such as retail establishments or movie theaters may be less likely to reduce air conditioning usage if it affects business. Customers may choose a different movie theater or store if the indoor temperature is above expectations. On the other hand, non-customer-facing establishments such as office spaces may be more willing to reduce peak usage if it is easier for employees to adapt.[28]

I classify establishments as customer-facing or non-customer-facing using the first two digits of their North American Industry Classification System (NAICS) industry code. To determine which two-digit industries are customer-facing, I use the U.S. Bureau of Labor Statistics classification of service-providing industries.[29] From this list, I define the set of service industries that are customer-focused. This list includes retail trade (NAICS 44-45), health care (NAICS 62), leisure and hospitality (NAICS 71), and accommodation and food services (NAICS 72). All other NAICS codes are classified as non-customer-facing. These include industries such as goods manufacturing (NAICS 11-31), transportation and warehousing (NAICS 48-49) and office spaces (NAICS 52-56).[30]

Table 6 shows the results from running the IV regressions separately for customer-facing and non-customer-facing industries. In all cases, the customer-facing industries do not show a significant response to peak pricing. This is in contrast to the non-customer-facing industries, where the impacts are larger than previously found when considering all industries together in Table 3. Inland customer-facing establishments show the largest response to peak pricing, reducing their peak usage by 17.9%. The result supports the hypothesis that customer-facing industries are less price-elastic. The result also highlights that most of the overall reductions from peak pricing are coming from the non-customer-facing establishments in inland California. In other states where peak pricing is not structured as an opt-out program, it may be optimal to target non-customer-facing establishments for enrollment to generate the largest program impacts.

[28]For example, an employer could inform their staff of an event day in advance and encourage them to dress for a warm office.

[29]http://www.bls.gov/iag/tgs/iag07.htm

[30]The NAICS codes that I have are often imprecise, which limits the ability to finely cut the data into many different industries. See Appendix Table A3 for a breakdown of establishments by two-digit NAICS code.

5.5 Coastal Event Days

Event days are determined based on the day-ahead forecasts for weather stations in the inland regions of California. Temperatures in the coastal region of California, however, are not highly correlated with inland temperatures. In many cases, peak hour average inland temperatures will reach 96 degrees Fahrenheit or more, while coastal temperatures remain below 70. In some years, this can result in a relatively cool set of coastal event days even with high inland temperatures. In 2014, inland temperatures were high while all but one of the event days on the coast were below 72.[31]

Previous sections have illustrated the role that temperature and air conditioning play in an establishment reducing usage on an event day. On cool event days on the coast, there is likely a lower demand for air conditioning on the coast. If air conditioning is playing a central role in an establishment's ability to respond to peak pricing, then it is possible that establishments are less responsive on cool event days. The relatively cool summer of 2014 on the coast suggests it may not be a good control group for estimating coastal peak pricing impacts.

To estimate program impacts on hot event days on the coast, I adjust my identification strategy to use only 2015 data. I replace the 2014 pre-period event days with a set of control days in 2015 when the temperature was relatively hot, but an event day was not called. The sample is limited to days where the average temperature for both event days and non-event days was above 72 degrees. This results in a set of the hottest 7 event and 15 control days of 2015, which I use to run the analysis.[32] I further limit establishments to those with consumption over 1600 kWh/month in the summer of 2014 in order to focus on establishments that are more likely to have air conditioning.

Table 5 shows the results from this modified regression specification for both the IV and RD specifications. The results show approximately an 8% reduction in usage for coastal customers when the appropriate set of control days is considered. These results highlight the role that temperature plays in an establishment's ability to respond to peak prices. When it is cool out, establishments run less air conditioning, which gives them a smaller margin on which to adjust their usage compared to a control group.

[31] See Appendix Table A2 for a breakdown of temperatures by event day and region.

[32] This approach would not work for inland customers; the event days are typically the hottest days of the summer, making the non-event days bad controls.

5.6 Aggregate Impacts

The previous subsections estimated the impacts of peak pricing on a subset of small C&I establishments in the PG&E service territory. Importantly, these customers are part of a utility-wide rollout that will place all small C&I establishments on peak pricing by 2018, which has the potential to generate large peak reductions.

To better understand the impacts of the fully deployed peak pricing program, I extrapolate my savings to all small C&I customers. There are three main assumptions that I make for this calculation. First, both the IV and the RD approaches reflect local average treatment effects. It is possible that the average treatment effect across all small C&I customers could be smaller or larger than those found here. Observationally, the establishments in the eight-week bandwidth are similar to those in a 27-week bandwidth, which is my complete sample.[33]

Second, these estimates capture only the short-run impacts of peak pricing in the summer of 2015. It is possible that establishment demand will become more elastic as peak pricing continues. For example, customer-facing establishments may be able to reduce peak consumption by upgrading their air conditioners to more efficient models or improving insulation. Third, I assume the estimated savings reflect future program year savings when there is no bill protection. This could result in my estimates understating aggregate impacts, as discussed in Section 5.1.

I extend the savings from both the IV and RD estimates using the results for inland customers from Columns (5) and (6) of Table 3. I focus on the inland establishments because coastal establishments only reduce their usage on a subset of the hotter coastal event days. I assume that the establishments in the eight-week bandwidth are representative of all small inland C&I customers, and that long-run opt-out rates will be similar to those observed in the first two years of my sample. I combine this with customer count information provided by PG&E to estimate the projected total impacts when the program is fully rolled out by the summer of 2018.[34] Using this technique, I find that small C&I establishments will provide reductions of 118 MW and 216 MW in peak load for the IV and RD approaches respectively.

6 Welfare Impacts of Peak Pricing

In this section, I first introduce a model to evaluate the welfare impacts of the peak pricing program, which I calibrate using the empirical peak demand reductions from the previous section. Using this approach, I consider changes to the current peak pricing program to better target the long-run investment inefficiencies that result from flat-rate pricing. I find

[33]See Appendix Figure A3 for a comparison of 2014 pre-period consumption across the two groups.

[34]A full accounting of the assumptions and calculations can be found in Appendix section E.1.

that, by changing when event days are called, and adjusting the event hour price, program outcomes can be greatly improved. I conclude by benchmarking the impacts of peak pricing against the first-best, real-time price using a simple theoretical energy pricing model.

6.1 A Model of Welfare Impacts from Peak Prices

The model is based on the current regulatory process in California, which is responsible for capacity construction decisions. Most other states follow a similar process. In the model, peak pricing reduces the level of summer peak demand, which in turn reduces long-run capacity requirements and saves costs by avoiding power plant construction. This framework allows me to calculate the welfare benefits of peak pricing in a manner that reflects how capacity decisions in electricity markets are made. The existing literature typically calculates the welfare impacts of alternative pricing policies using a stylized model of electricity prices and power plant construction (Borenstein 2005, 2012; Borenstein and Holland 2005; Holland and Mansur 2006). These models provide insight on the welfare impacts of alternative pricing policies, but use assumptions that do not realistically portray the nature of the binding capacity constraint in electricity markets.

The structure of electricity markets is defined by the lack of cost-effective storage, which requires supply and demand to be balanced in real time. This feature introduces a capacity constraint equal to the total capacity of generators; blackouts will result if demand exceeds this constraint at any time. The stylized models of electricity markets do not consider this constraint, and assume that the price and demand for electricity are able to adjust quickly enough to avoid shortfalls. Additionally, such models assume a cost to build new generators, but not construction time. In practice, it can take six years from the initial proposal for a power plant to begin generating electricity. Much of this process is governed by the regulator that sets the amount of generation capacity that a utility must have on hand to avoid blackouts. The stylized models used in the literature do not reflect the complexities of the regulatory process and how this impacts electricity market outcomes.

I introduce a model based on the actual "resource adequacy" process, where the regulator mandates how much peak generation capacity the utility must have on hand (Joskow and Tirole 2007).[35] These peak capacity requirements are typically met by building specialized "peaker" power plants, which have a low capital cost but a high marginal cost of generation. Some of these plants run for only a few hours on the hottest day of the year. A large amount of peaker capacity is expensive to build and maintain.

[35]The process I model is based on the California resource adequacy process, but is representative of how capacity requirements are set in most states.

Typically, the regulator forecasts future peak demand using historical data and load growth projections. Using this forecast and a valuation of blackouts, they set a resource adequacy level for the utility in the coming year. The model I introduce is based on how peak pricing changes the resource adequacy process. The model proceeds in three steps that happen yearly.

In step 1, no peak pricing program has been implemented. The regulator has information about the distribution of historical peak loads and temperatures, which also includes information about the peak load from the previous summer. I denote this information set as L_0. The regulator uses this information to determine how much peak capacity is needed, using the decision function F(), which does not change over time.[36] I assume this is a well-defined process known to all market participants, and that the regulator sets capacity high enough that there will be no generation shortages in the coming year.[37] I define this peak capacity requirement as $X_1 = \mathrm{F}(L_0)$.

In step 2, the utility acquires capacity X_1 at cost $\mathrm{C}(X_1)$. I assume that the utility must fulfill this requirement and that the regulator perfectly observes the utility's behavior. The cost function is linear and does not change over time. For simplicity, it reflects the utility's yearly cost to acquire capacity.

Step 3 is when the demand for the year is realized. In the absence of peak prices, demand would have reached a peak level of L_1. However, with the implementation of peak prices and their corresponding demand reductions, the new load is $\widetilde{L_1}$, such that $\widetilde{L_1} < L_1$. For simplicity, I assume peak pricing reduces peak load on all event days in a summer by the same amount, and that this amount remains constant from year to year.

The majority of the benefits from peak pricing come from this reduction in summer peak demand. This can be seen in Panel A of Figure 9, using a simplified peaker capacity supply curve. By reducing the total peak demand, peak pricing reduces the total generation capacity necessary to satisfy demand. This saving in capacity cost reflects the high costs associated with building generation capacity and is the main driver of savings under the peak pricing program.

[36] If the regulator were an optimal social planner, the F() decision function would balance the benefits of reliability against the costs of acquiring capacity, and pick an optimal capacity requirement for the utility. In practice, most regulators are risk averse and put a very high cost on supply shortfalls that result in localized blackouts. As a consequence, regulators typically set very high reserve requirements for utilities. I do not take a stand on the exact approach the regulator should use. I simply assume they follow the same rule each year.

[37] Blackouts from demand exceeding capacity are rare. The current California process requires capacity at 1.15 times the projected peak load. This level is sufficiently high to assure that capacity limits will never be reached. See Joskow and Tirole (2006) and Joskow and Tirole (2007) for a discussion of optimal capacity with the possibility of rationing.

The second impact from peak pricing is the surplus loss that results from changes in customer behavior when paying higher prices on event days. For example, establishments may choose to run their air conditioner less, leading to a less comfortable indoor environment. This impact can be seen graphically in Panel B of Figure 9. To calculate this impact, I first recognize that the electricity still sold at the peak price (to the left of Q_1) induces no change in total surplus, as it is just a transfer from consumers to producers. For units that go unsold due to the price increase (to the right of Q_1 and to the left of Q_0), the change in surplus is the area under the demand curve minus the resource savings from not producing these units. In this case, the resource savings are equal to the fuel savings of the peaker plants that would otherwise be used to generate this electricity.

I value the reduction in fuel used to run a peaker plant at its short-run marginal production cost (SRMC), which I assume to be \$.102/kWh based on current natural gas prices (California Energy Commission 2015). I use the SRMC for this calculation because I assume the regulatory process dictates that sufficient capacity is available at all hours of the year, meaning the surplus losses are net of the short-run costs associated with running a peaker plant. This set of calculations leaves what I term the net consumer surplus loss, which is represented by the shaded triangle in Panel B of Figure 9. I use a linear demand curve for simplicity and because it provides a conservative upper bound on the net CS losses compared to other concave alternatives such as a constant elasticity of substitution demand curve. I define the net consumer surplus loss in year 1 as CS_1.

The process now restarts at step 1 in year 2. In the world with peak pricing, the regulator observes peak load $\widetilde{L_1}$ and sets peak capacity requirements for the coming year $\widetilde{X}_2$ = F($\widetilde{L_1}$). In the non-peak pricing scenario, the regulator observes peak load L_1, resulting in peak capacity requirement $X_2 > \widetilde{X}_2$. In step 2 of year 2, the utility must acquire capacity at cost C($\widetilde{X}_2$) and C(X_2) for the peak and non-peak pricing scenarios, respectively. This process continues and repeats for both scenarios over time.

To calculate the welfare impacts of the peak pricing program, I subtract the costs in the peak pricing scenario from the costs in the non-peak pricing scenario. The benefits are calculated over T periods on N event days per year using discount rate r. The change in welfare from implementing peak pricing is defined as follows:

$$\Delta Welfare = \sum_{t=1}^{T} \frac{C(X_t) - C(\widetilde{X}_t) - N \times CS_t}{(1+r)^t} \tag{5}$$

This calculation compares the cost of peak generation capacity with standard pricing to the lower peak capacity needs when peak prices are used.

The model in this section leans on a stylized formulation of net consumer surplus losses. It considers only the surplus losses to establishments that occur between 2:00 pm and 6:00 pm on event days, when prices increase. It is possible that customers are responding to peak prices in ways that that are not reflected in these hours. For example, Section 5.2 shows that peak pricing enrolled establishments reduce their usage before the 2:00 pm-6:00 pm event window starts. The model presented here does not capture the net consumer surplus losses associated with this change in behavior before the event window, or any other non-event window impacts. Bill protection could also impact the magnitude of the net consumer surplus losses. If the price signal to establishments is potentially affected by bill protection, then the response to peak pricing may not reflect the true net consumer surplus impacts. I conduct robustness checks using different levels of CS losses to see how these factors impact the welfare estimates.

6.2 Calculating Welfare Impacts of PG&E's Peak Pricing Program

In this section, I calculate the welfare impact of the PG&E peak pricing program using the model from the previous section and my empirical results.[38] Some of the simplified assumptions in the model are adjusted to better reflect the PG&E service territory. In the model, the utility purchases 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 (CEC) estimates it costs $1,185,000/MW to build a natural gas combustion turbine peaker plant (California Energy Commission 2015).[39] Using these plant construction numbers and my empirical estimates, I find that the peak pricing program would provide a one-time saving of $139 million in construction costs with the IV approach. 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 $3.05 million per year.

To make the CS loss calculation, I use a linear demand curve as discussed in the previous section. One important difference between the model and PG&E prices is that retail

[38]From this point forward, I present calculations using only the IV estimate from inland establishments for simplicity. Appendix Section E.2 outlines why I make this choice and the welfare benefit calculations using the RD estimates.

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

electricity rates for small C&I customers are set at \$.25/kWh. Retail prices are higher than the short-run marginal cost of production because fixed costs are recovered volumetrically in PG&E. In the previous section, I set retail rates at the short-run marginal cost of production, which I assume to be \$.102/kWh for a peaker plant (California Energy Commission 2015). Establishments were willing to pay the \$.25/kWh price for their electricity during these peak periods, meaning economic surplus is lost on event days when prices are increased and consumption is reduced. Graphically, this impact is represented by a rectangle between the \$.25/kWh electricity price and the \$.102/kWh short-run marginal cost of production. The total CS loss from peak pricing is this rectangle plus the triangle under the demand curve, shown in Figure 9.[40] Using my empirical estimates, I find that the total net consumer surplus loss in 2015 equals \$3.14 million/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.[41] Using my elasticity estimates and linear demand, I calculate these welfare gains to be \$0.84 million/year.[42]

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. This results in total welfare benefits of \$154 million (2016 dollars) using a 3 percent real discount rate and a 30 year horizon.[43] These numbers represent the welfare benefits of running the peak pricing program every summer for 30 years. Embedded in this back-of-the-envelope calculation is the assumption that electricity supply and demand will not change in ways that affect the numbers calculated above. I also assume that the operation and maintenance costs stay constant over the life of the plant, which likely understates the costs as the plant ages. Furthermore, establishment demands are likely to become more elastic as they face peak prices over many summers.

The above welfare calculations only capture the negative net consumer surplus impacts from peak pricing that occur between 2:00 pm and 6:00 pm. Establishments may undertake behaviors that affect consumption outside of the event window, resulting in welfare impacts that are not captured with this model. Bill protection may also impact the welfare estimate

[40] Appendix Figure A5 shows the CS loss triangle and rectangle that reflect PG&E prices.

[41] Importantly, this price reduction is welfare-improving because the retail price of electricity for small C&I customers exceeds any reasonable social cost.

[42] 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.

[43] The results are not very 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.

by affecting consumer response to the peak price. For robustness, I consider a scenario where the net consumer surplus impacts are double what is calculated above. Using this assumption, I find the total welfare impacts of the program to be $108 million. This shows that, even under a conservative set of assumptions, the welfare impacts of peak pricing remain positive.

PG&E is one of three major utilities in California, along with Southern California Edison and San Diego Gas and Electric, to implement peak prices under order of the Public Utilities Commission. As a result, most of California is in the process of implementing opt-out peak prices for C&I customers. I use my estimates to inform the impacts of the larger rollout across the state. The first row of Table 7 shows the welfare impacts of peak prices for small C&I customers. Columns (2) and (3) show the PG&E savings estimates extended to the three major investor-owned utilities (IOU) and for the full state, respectively. I find that the IOU-wide benefits total $394 million while the California-wide benefits are $573 million over a 30 year period. There are a number of assumptions used to make these welfare calculations. First, I assume that small C&I customers in PG&E are similar to those in other regions. This may be a reasonable assumption in California, but it is likely less true for the full U.S. grid. Column (4) shows the savings estimates extended out to the national grid, showing a potential $17 billion benefit of this policy. This number represents the impact only for small C&I establishments, which I assume to be 10% of peak load across the U.S. The magnitude of this estimate highlights the significance of the distortion caused by flat retail pricing.[44]

The second row of Table 7 considers the impacts for the full set of C&I customers. I assume the same 13.4% reduction in peak usage for all of these customers as I estimated for the small C&I customers.[45] The welfare estimate is likely a lower bound, since peak pricing adds $1.20/kWh to the price of electricity for large C&I customers on event days rather than the $.60/kWh for small establishments. Extending this estimate nationally results in a $82 billion savings estimate. This estimate assumes that the national C&I makeup of the U.S. reflects California. This large potential welfare benefit provides perspective on the size of the distortion that flat retail prices introduce.

6.3 Targeting the Capacity Constraint

The PG&E peak pricing program is designed in a manner similar to other peak pricing policies around the U.S. The utility has discretion over when to charge higher prices on 9 to 15 event days per summer. In this section, I consider the welfare implications of how event days are chosen and the price charged during event hours. I do this in the context of the

[44]See Appendix Section E.3 for the data and assumptions used in these calculations.

[45]I adjust the savings estimates for the 43% of large C&I customers that have opted out of peak pricing since it was first introduced in 2010.

current peak pricing program, where resource adequacy requirements guarantee that there will be sufficient capacity available to avoid blackouts.

PG&E calls event days using day-ahead weather forecasts. When the average forecasted temperature for inland California exceeds a trigger temperature of 96 or 98 degrees, an event day is called. The trigger temperature is based on how many event days have been called so far in a given summer and on historical weather trends.[46] This approach is effective at selecting the top 12-15 demand days each summer, but it is not designed to maximize the net benefits of the peak pricing program.

The typical summer in California has a small number of days with very high demand that are responsible for peak load. For example, the difference between the demand on the highest event day and the median event day in 2015 was 1,220 MW, more than 14% of total peak load.[47] The few highest demand days each summer drive resource adequacy requirements and the long-run construction of peaker plants. I define as "super-peak" days the set of days each summer for which calling an event day reduces the total summer peak load. The number of super-peak days each summer depends on both the level of reduction due to peak pricing and the number of high-demand days.[48] Most Northern California summers have between one and three super-peak demand days based on the estimated reduction due to the peak pricing program for small C&I customers.

The role of super-peak days in the 2015 program can be seen in the first two columns of Table 8. To project the impact that the peak pricing program for small C&I establishments will have once it is fully rolled out, I use the aggregate 118 MW reduction that projects outcomes for 2018. This reduction would lower the 2015 summer peak from 19,451 MW to 19,333 MW, which would become the new summer peak $\widetilde{L}_t$. In 2015, no event days other than the one with the highest demand will affect $\widetilde{L}_t$. For example, reducing the load on September 9, 2015 from 19,017 MW to 18,899 MW will not affect $\widetilde{L}_t$ and will not provide savings in long-run generation capacity investment.[49]

Table 8 shows the 2015 event days with the welfare impacts broken out. These values reflect the welfare impact associated with each event day in 2015, using the ex-post information about the realized demands. In practice, the peak pricing program is based on day-ahead forecasts, which introduces significant uncertainty about which event days will provide benefits

[46] The trigger temperature is adjusted every 15 days throughout the summer to hit the target number of 12 to 15 event days. See Appendix Section A for more details.

[47] The same pattern holds for all years 2010-2015, with the difference between maximum and median peak load of 1,600 MW.

[48] If the reductions from peak pricing were larger, then there could be more super-peak days each summer where calling an event day would reduce peak load $\widetilde{L}_t$. For example, the number of super-peak days could go up if the large C&I establishments were included in the calculation.

[49] A list of the top 20 demand days in 2015 can be seen in Appendix Table A4.

when they are called. Column 3 shows the capacity value of reducing peak load. Only the highest demand event day of the summer provided capacity cost savings, because none of the other event days affect summer peak load. Column 4 shows the net consumer surplus loss figure of $209,000 per event day, which is reported in the same discounted manner to allow for easy comparison. All of the non-super peak event days reduce the welfare impacts of the program without providing capacity cost savings.

The cost of non-super peak event days quickly adds up. Each extra event day that does not provide capacity cost savings results in a loss of $4.2 million of net consumer surplus over the life of the program. A refinement to the peak pricing program would call just the super-peak event days each summer.[50] This approach is challenging with event day programs because it is not possible to forecast ex-ante which summer days will be super-peak (Borenstein 2012). Despite this limitation, there are a number of improvements that could be made to the current program using the day-ahead information that is available to PG&E.

One simple change to the peak pricing program is to tighten the criterion used to call an event day. The second to last column of Table 8 shows the day-ahead temperature forecasts for the inland region of California. An event day is called when this temperature equals or exceeds the "trigger temperature" set by PG&E, which is shown in the last column.[51] The current set of trigger temperatures typically calls the super-peak demand days each summer, but also includes a large number of additional days that do not provide capacity cost savings. A simple adjustment to the peak pricing program would move the trigger temperature to 101 degrees and remove the current 9 days per summer minimum. This approach uses the same day-ahead temperature forecast that PG&E currently uses to pick event days. It would result in a program that is better targeted at the super-peak event days, and would result in fewer low-demand event days each year.

In an electricity market with regulated resource adequacy requirements, the impacts of missing a super-peak event day are a higher summer peak $\widetilde{L}_t$ and the costs of building capacity in a future period. In most cases, the welfare loss from missing a super-peak event day is much higher than the benefit of avoiding a non-super peak event day. Any day-ahead program must take this tradeoff into account. The proposed 101-degree trigger temperature accurately selects the super-peak event days over the last five years using day-ahead temperature forecast data, but a different trigger may be preferred in the future. For example, climate change

[50]It may be useful to set a minimum number of event days so that establishments do not forget they are on the program. I have not found any research that identifies the impact of using too few event days.

[51]See Appendix A for more details on trigger temperatures.

may impact the intensity and frequency of high temperature days, which could necessitate a further refinement.[52]

The second dimension of the peak pricing program that could be adjusted is the level of the event day price. Currently, small C&I establishments pay \$.85/kWh during event windows, which is \$.60 higher than their typical rate. Wholesale prices are routinely above \$.85/kWh, and the peak price for large C&I PG&E establishments is set at \$1.35/kWh. This level is designed to reflect the long-run value of capacity and is based on the regulator's avoided cost of capacity (California Public Utilities Commission 2001). There is no reason to charge different event day prices to different customer classes, because both are subject to the same capacity constraint that drives system costs. If \$.85/kWh is below the efficient wholesale cost of electricity on event days, there are potential welfare gains from raising the event day price for small C&I establishments.

I quantify the welfare benefits of changing the number of event days and level of peak prices in Table 9. To estimate the impact of higher prices, I assume a linear demand curve, as in the previous section, and extend the results from the current peak pricing program. The current peak pricing program has an event price of \$.85/kWh on 15 days per year and is shown in the top left entry. Column (2) shows outcomes if the small C&I peak price were raised to \$1.35/kWh, the level paid by large establishments. It shows that using the current 15 event days per summer and increasing the event price from \$.85/kWh to \$1.35/kWh would increase the welfare benefits from \$154 to \$204 million. The third column shows the impacts of a peak price set at \$1.85/kWh.[53] Moving down the table decreases the number of event days per summer from 15 to 8 to just the 3 super-peak days.[54] The table shows that moving to a 101 degree trigger and using the large C&I peak price of \$1.35/kWh – both of which are realistic adjustments – could improve program outcomes by 87%.

6.4 Comparing Peak Pricing to First-Best Policy

To put the second-best peak pricing program in perspective, I compare outcomes to the first-best alternative. Real-time pricing has been shown by previous research to result in efficient long-run outcomes, making it a useful benchmark (Borenstein 2005; Borenstein

[52] I also considered more complicated regression-based event day models using load forecasts, but this adds unnecessary complexity without additional insight. A lower trigger may also be optimal when including the reductions from large C&I establishments, which can increase the set of super-peak days through larger reductions.

[53] The calculations assume that peak wholesale prices are greater than or equal to the peak price in each column. If, for example, peak prices only reached \$1.50/kWh, then the results in Column (3) would overestimate the benefits.

[54] The estimated impacts assume that the super-peak days are correctly called as event days under all three approaches. Forecasting errors could reduce the benefits if a super-peak event day is missed.

and Holland 2005). For this exercise, I consider a theoretical energy-only electricity market where electricity supply and demand are cleared continuously with a uniform price auction.[55] I assume long-run capacity construction decisions are made through the resource adequacy process outlined in the previous sections.[56]

With real-time prices, customers face retail rates that change every five minutes to reflect the real-time wholesale cost of electricity. I assume customers are fully informed about the real-time price they are paying, and that their usage reflects the five minute price.[57] To allow a simple comparison between peak pricing and a real-time price, I assume the wholesale price takes on two distinct values. The low price reflects the marginal cost of generation at high-efficiency natural gas power plants, which I set at \$.10/kWh. When demand exceeds the capacity of the low-cost plants, the price of electricity spikes to the high level.[58] The high price reflects the long-run cost of generation, which includes the costs of building and running peaker power plants to meet demand. I assume a high real-time price of \$1.35/kWh, which corresponds to the peak price paid by large commercial and industrial customers in the existing program. When demand drops to a level where the base load capacity is sufficient to balance load, the price returns to the low price level.

I benchmark outcomes under the peak pricing program against the benefits under real-time pricing. I first consider the existing peak pricing program, where prices are increased to \$.85/kWh between 2:00 pm and 6:00 pm on 15 event days per summer.[59] This can be seen in Panel A of Figure 10. The well-targeted peak pricing program uses the optimal event hour price of \$1.35/kWh on only eight event days per year.[60] This can be seen in Panel B of Figure 10. In both scenarios, I assume there are three super-peak event days each summer that provide capacity savings, and that these will be called as event days under both systems.

[55] I use a simplified market design because the California electricity market has a wholesale price cap of \$1.00/kWh, as well as secondary markets for providing capacity, which make the comparison challenging.

[56] The first-best outcome reflects any inefficiencies that may exist in the resource adequacy capacity investment process.

[57] Real-time pricing programs could have prices vary as frequently as every minute or in larger 15-30 minute increments. Joskow and Tirole (2006) suggest that customers may not respond to short-run changes in electricity price if transaction costs are too high. They suggest that this cost will be reduced through the use of advanced technologies that can quickly take advantage of price variation.

[58] This pricing structure reflects a retail electricity model with fixed charges, where the retail rate reflects the marginal cost of generation. Depending on natural gas prices, the cost at a high-efficiency natural gas power plant may be lower than \$.10/kWh. A full accounting of the assumptions can be found in Appendix Section E.4.

[59] I assume 15 event days will be called each summer, to reflect the summer of 2015 for which peak pricing impacts were estimated.

[60] It may be ideal to set the peak price slightly below \$1.35/kWh due to the net consumer surplus loss caused by peak pricing. For simplicity, I assume the well-targeted peak price is set at \$1.35/kWh. I use the temperature trigger proposed in Section 6.3 to select eight event days per summer.

During the super-peak days, I assume the price is at the high level for five minutes between 2:00 pm and 6:00 pm.[61]

The model outlined for this calculation is stylized in nature and makes a number of simplifying assumptions that could impact outcomes. Real-time prices typically vary throughout the day and year to reflect transmission constraints, variation in short-run marginal generation costs or other system costs. Peak prices, by having only two possible price levels on a set number of event days, are not able to capture the benefits from this type of price variation. Ultimately, these impacts are likely small compared to large capacity savings benefits from reducing peak load.

To compare peak-pricing to first-best, I use my empirical estimates to calculate the welfare gains under peak pricing and compare them to the outcomes under real-time pricing.[62] For the existing peak pricing program, the difference between first and second-best comes from two sources. First, by charging an event price below \$1.35/kWh, peak pricing will generate lower capacity construction savings than will real-time pricing. Second, under the current peak pricing program, the event price will be charged for 60 hours per year compared to just 15 minutes under the real-time price. I choose a short period of time during which real-time prices are at the high level in order to remain conservative in reporting the benefits of peak pricing compared to real-time pricing. The longer the high event price is charged while real-time prices are low, the lower the relative benefits that peak pricing provides. The well-targeted peak pricing program, by setting peak prices at \$1.35/kWH, provides the same capacity construction savings as the real-time price. The lower number of event hours each year (32) also reduces the extra net consumer surplus loss that comes from non-super peak event days.

Using this approach, I find that the current peak pricing program provides 43% of the welfare benefits of the first-best approach. The result illustrates that the current program is providing some value, but performs poorly compared to the first-best policy. The well-targeted peak pricing program is able to make significant welfare improvements, delivering 80% of the first-best outcome. This result underscores the value of targeting. In markets with a binding capacity constraint, directly targeting the distortion caused by the constraint is an effective tool to improve welfare.

[61] The short length of time at peak is a conservative assumption with respect to the value of peak pricing. I consider longer periods of peak prices as a robustness check.

[62] I use the same elasticity for both the peak pricing and real-time price reductions. I assume customer response to the high price will be the same whether they face the high price for a short time or the full peak window. Wolak (2011) showed that, for residential customers, the response to peak prices was similar using both a short and a long event window.

The results of the benchmarking analysis depend on both the empirical estimates and the modeling assumptions. The empirical estimates inform the level of capacity savings and the net consumer surplus loss from charging a higher price. There are a number of modeling assumptions that can affect the levels of the benchmarking numbers, but do not significantly shift the qualitative results. First, I assume the peak price is 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. If the optimal event day price were higher, it would reduce the effectiveness of the peak pricing program compared to real-time pricing. Second, the assumption that real-time prices are at peak for only 15 minutes per year underestimates the relative value of peak pricing compared to real-time pricing.[63] Third, the current approach measures net consumer surplus loss only between 2:00 pm and 6:00 pm on event days. If net consumer surplus losses from peak pricing were higher, the relative benefits of peak pricing would be lower.[64]

The benchmarking model is useful in understanding the impacts of poorly targeting the peak pricing program. Table 10 shows a number of alternate scenarios that consider how an incorrectly targeted peak pricing program might perform. As before, I assume the high real-time price is \$1.35/kWh. Column (1) mirrors the current program, where peak prices are set at \$.85/kWh; Column (2) shows the results for the correctly chosen peak price; and Column (3) shows the impacts if peak prices were set too high, at \$1.85/kWh. The first row shows the outcome when eight event days are chosen per year using the 101 degree trigger of the well-targeted program. The second row shows the outcomes with 15 event days. The bold entries correspond to the current and well-targeted peak pricing programs discussed previously. The other entries show the consequences of poorly targeting the peak pricing program.[65]

The benchmarking model shows that, while the returns to targeting can be large, the downsides to incorrectly targeting are also significant. Setting the wrong price or calling too many days reduces program effectiveness. For example, calling 15 event days per year at a price of \$1.85/kWh would capture only 19% of the first-best outcome. The results highlight the value that empirical research can provide in measuring program outcomes and using these estimates to further improve the program. The ability to design a well-targeted program depends on the aggregate peak pricing reductions, combined with knowledge of institutional details to value the costs and benefits of the program. Using these insights helps inform the

[63] This assumption has a relatively small impact on outcomes. For robustness, I consider the extreme case where real-time prices are at the peak for all four hours between 2:00 pm and 6:00 pm. Using this assumption, the benefits of the current program would be 46% of the first-best policy.

[64] I find that, when net consumer surplus losses are doubled, the current program and the well-targeted program provide 32% and 60% of the benefits, respectively.

[65] See Appendix Table A12 for a robustness check where prices hit the peak for the full four-hour period between 2:00 pm and 6:00 pm.

best way to target the costly capacity constraints by observing the underlying structure of peak-event days on the PG&E grid. The estimation of the short-run electricity demand curve allows me to balance the net consumer surplus losses under peak pricing against the capacity cost savings from higher prices. Taken together, these results suggest that it is possible to achieve four-fifths of the first-best outcome using a well-targeted, second-best policy.

7 Conclusion

Retail electricity customers in the U.S. are typically charged a flat price per kWh consumed. This time-invariant price does not reflect the cost of capacity at peak demand hours. This paper studies a policy, peak pricing, that charges higher prices to retail customers on high-demand days when it is more costly to supply marginal units of electricity. Using quasi-random variation in program implementation and two different identification strategies, I find that establishments reduce their usage between 2:00 pm and 6:00 pm by 13.4%. In the aggregate, the peak pricing program will provide 118 MW of peak demand reductions in the PG&E service territory when fully implemented. The peak savings reduce the amount of generation capacity required at peak, yielding $154 million of welfare benefits. I compare outcomes to a theoretical first-best, real-time pricing policy, finding that the current program captures 43% of the benefits. I show that a well-targeted peak pricing program could provide greatly improved outcomes, equaling 80% of the first-best outcome.

This paper fills an important gap in the literature by providing the first evidence of how commercial and industrial customers respond to peak pricing. This is particularly important as the popularity of peak pricing programs continues to grow, fueled by the installation of low-cost, advanced metering technology. Further research is required to better understand the impacts of peak pricing on large C&I customers. They constitute over 50% of California and national electricity demand, making their response to peak prices important for future energy policy.

The approach I take in this paper is relevant to a wide range of markets where prices do not reflect the cost of capacity constraints at peak demand periods. I use empirical estimates of a second-best pricing policy to make welfare calculations and compare outcomes to the first-best alternative. This framework could be used to evaluate and improve other second-best policies. For example, most bridge tolls do not adjust to accurately reflect congestion costs at peak commute hours. In the long run, this may lead to the construction of excess transportation infrastructure, similarly to the manner in which flat electricity pricing leads to excess generation capacity. More work in these and related settings will help to validate these insights and can lead to the improvement of other second-best policies.

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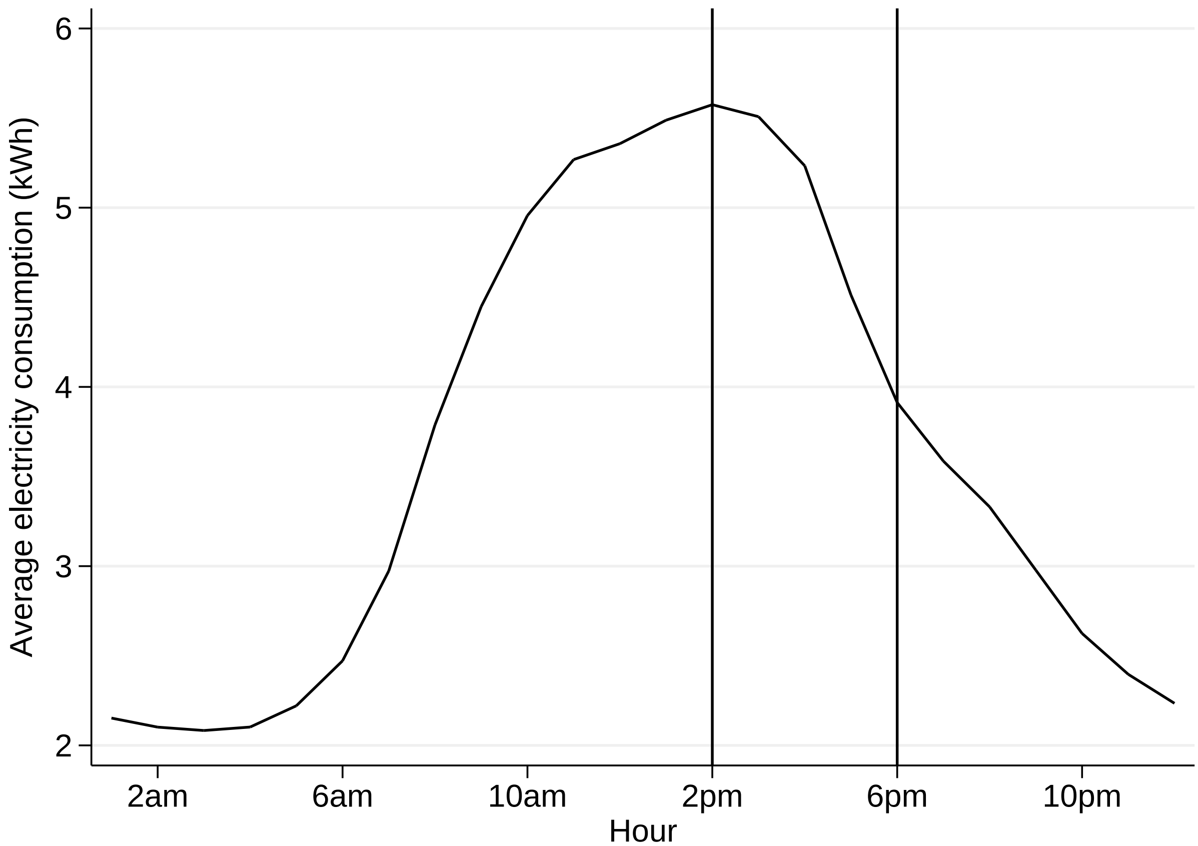
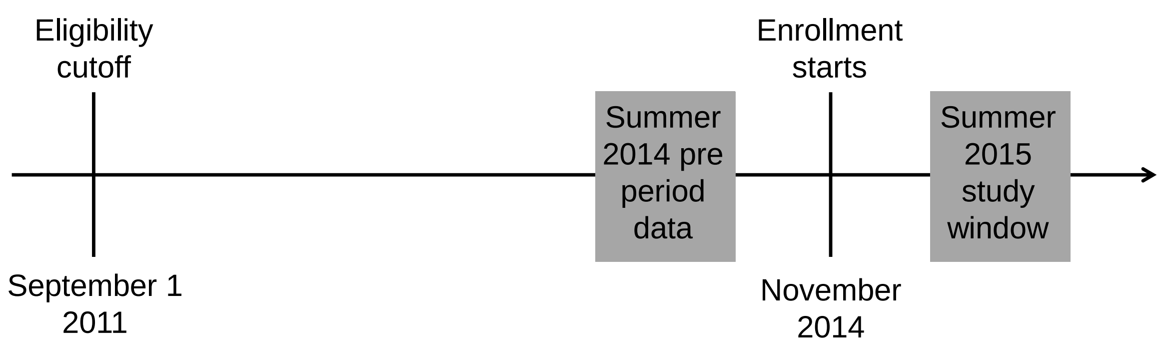
Figures

Figure 1: Average Consumption Profile of Small Commercial and Industrial Establishments in Sample



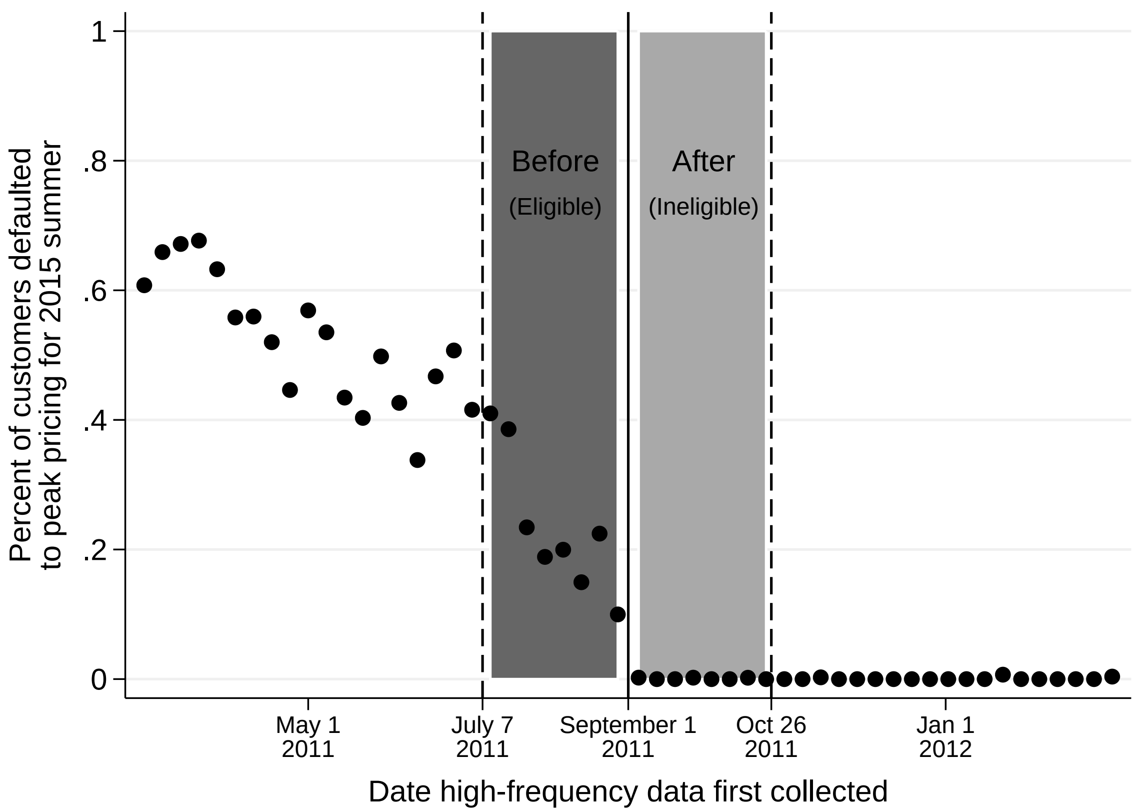
Note. - This figure shows the average consumption profile of the establishments in my analysis for all weekdays during the summer of 2014. The vertical lines signify the beginning (2:00 pm) and end (6:00 pm) of the peak event window. The system peak demand for the PG&E grid typically is between 4:00 pm and 6:00 pm.

Figure 2: Timeline of Peak Pricing Rollout



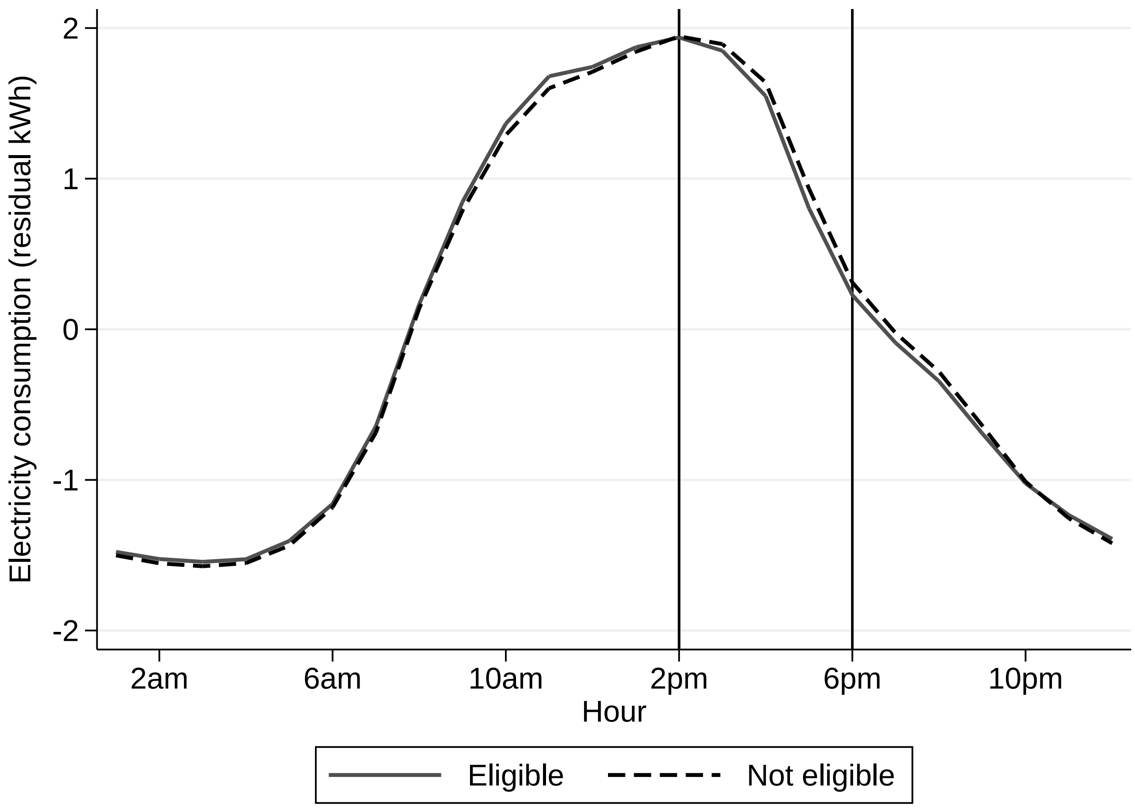
Note. - This figure shows the timeline of peak pricing implementation. I classify establishments as eligible for peak pricing in 2015 if their high-frequency metering data began before September 1, 2011. Enrollment in opt-out peak pricing starts November of 2014 for the summer of 2015. Final treatment status is determined by eligibility and technical requirements, which are described in Section 4.1.

Figure 3: The Effect of Eligibility on Peak Pricing Treatment Status



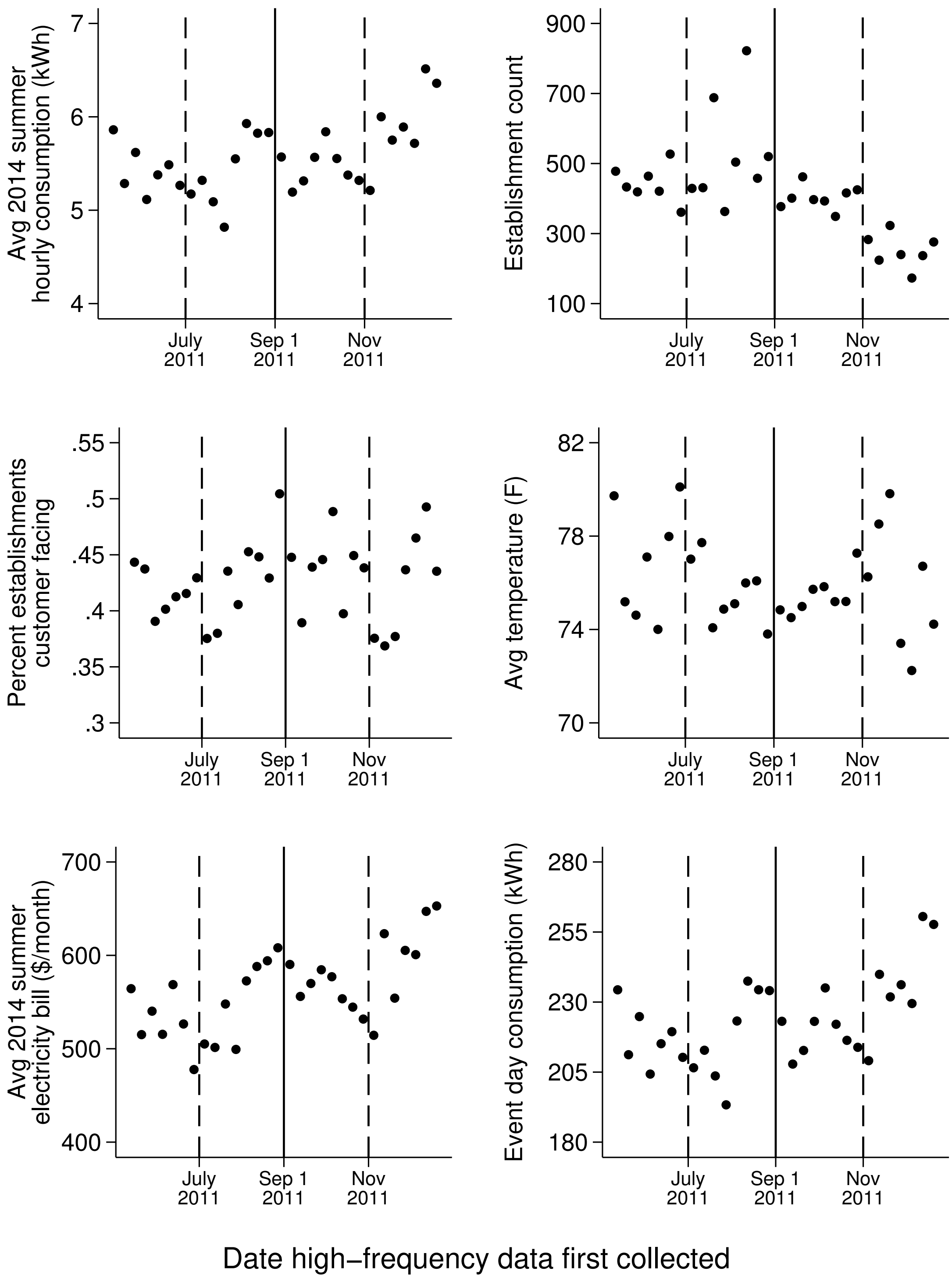
Note. - This figure shows the impact of peak pricing eligibility on treatment. Establishments are binned by the week their high-frequency data began. Establishments to the left of the September 1, 2011 threshold are peak pricing eligible. There are around 500 establishments per bin. The figure shows 27 weeks in each direction from the threshold to show the larger default patterns. The vertical dashed lines represent the eight-week bandwidth used in the main specification.

Figure 4: Pre-Period Electricity Consumption by Eligibility Group



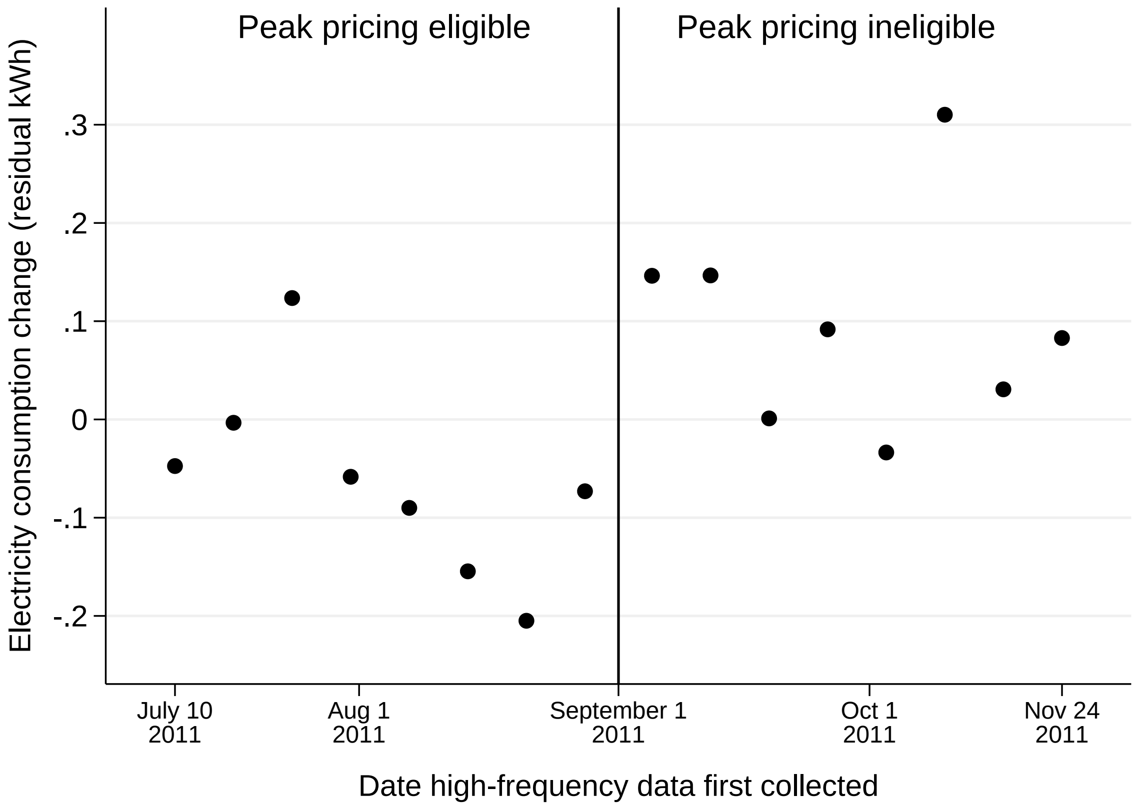
Note. - This figure shows the 2014 pre-period average hourly consumption for peak pricing eligible and ineligible establishments. Consumption is shown conditional on establishment fixed effects. I cannot statistically reject that the pre-period consumption is the same for both groups using hour-by-hour t-tests. The vertical lines signify the beginning (2:00 pm) and end (6:00 pm) of the peak event window.

Figure 5: Smoothness of Observable Characteristics through the September 1, 2011 Threshold



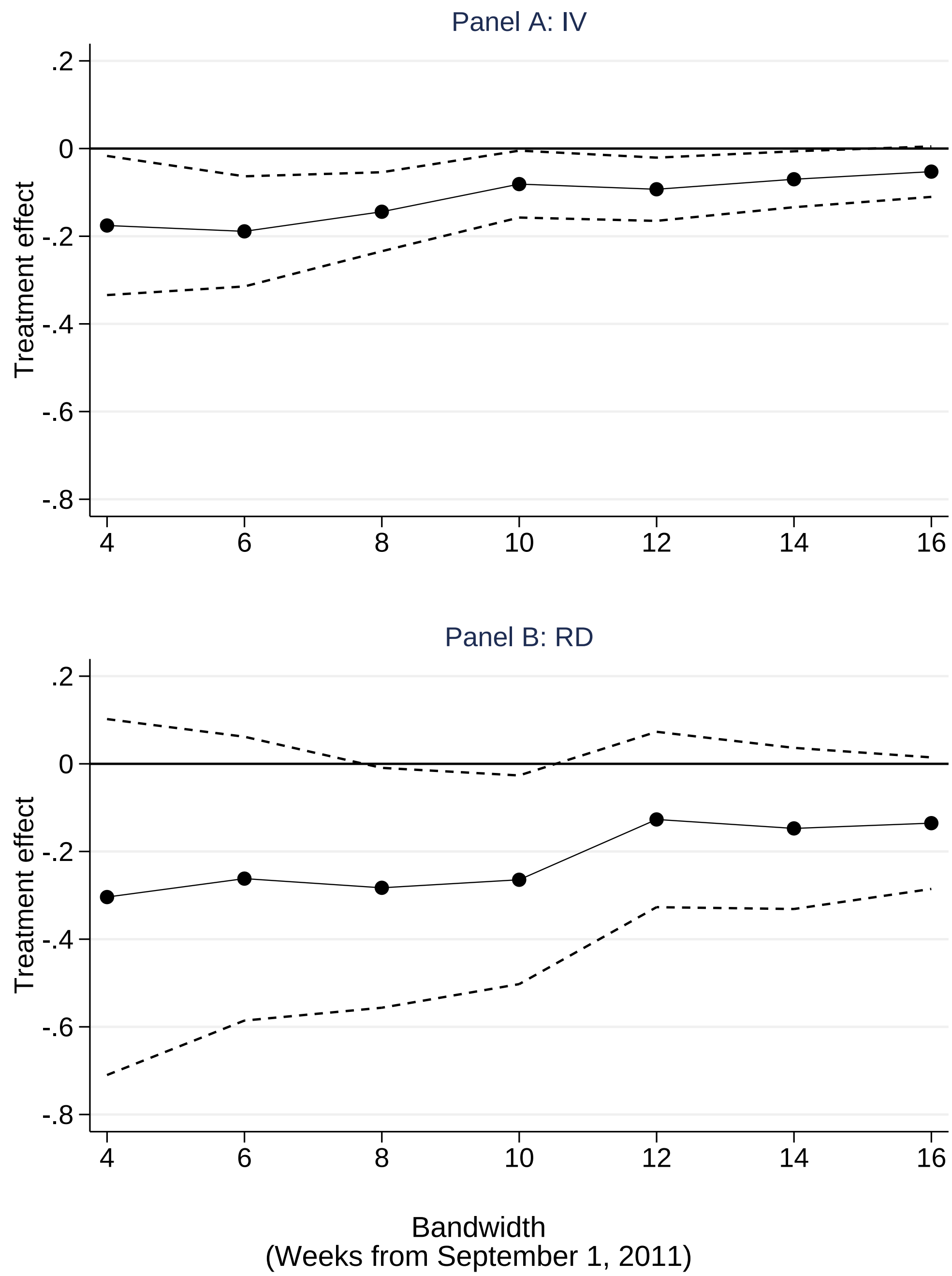
Note. - This figure shows trends in observable characteristics near the September 1, 2011 discontinuity, shown with the solid black vertical line. The vertical dashed lines indicate the eight-week bandwidth used in the main specifications.

Figure 6: The Impact of Peak Pricing Eligibility on Inland Establishment Peak Consumption (Reduced Form)



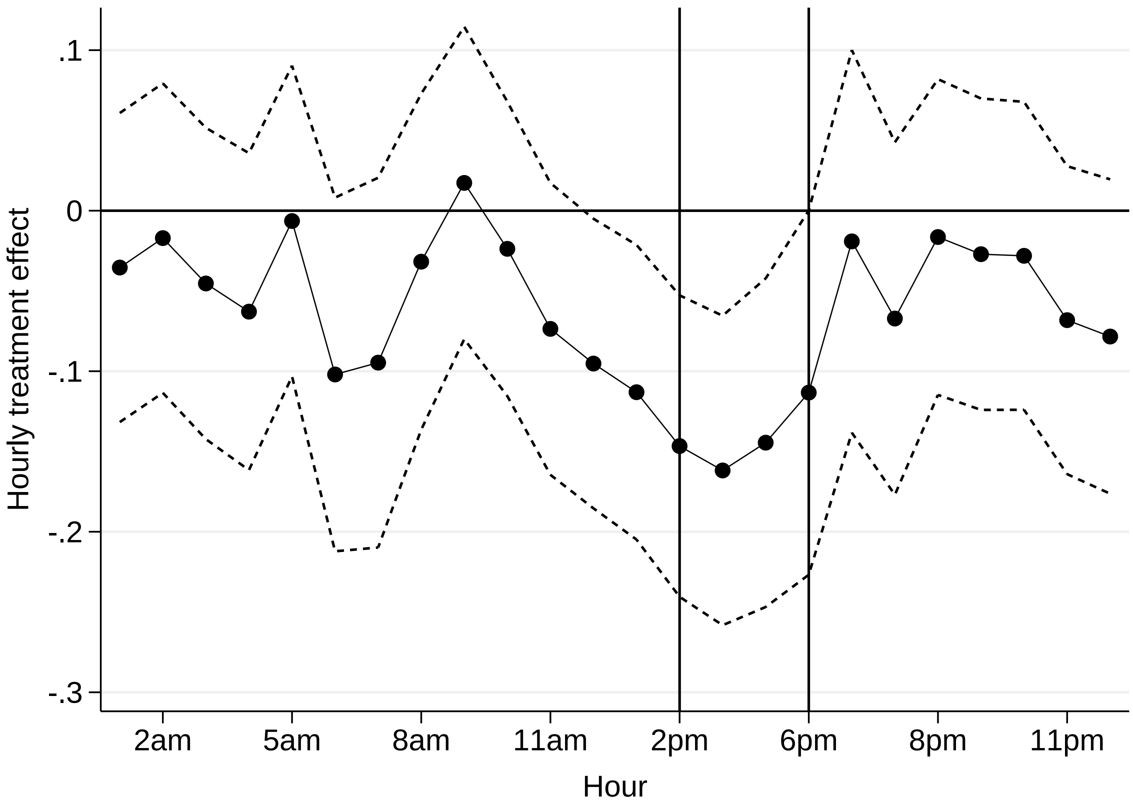
Note. - This figure shows the reduced form impact of peak pricing eligibility on consumption between 2:00 pm and 6:00 pm on event days. Each dot represents the difference between 2015 and 2014 peak consumption by bin, conditional on establishment and hour-of-sample fixed effects. The figure shows the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

Figure 7: Treatment for Inland Establishments Effects Estimated at Varying Bandwidths



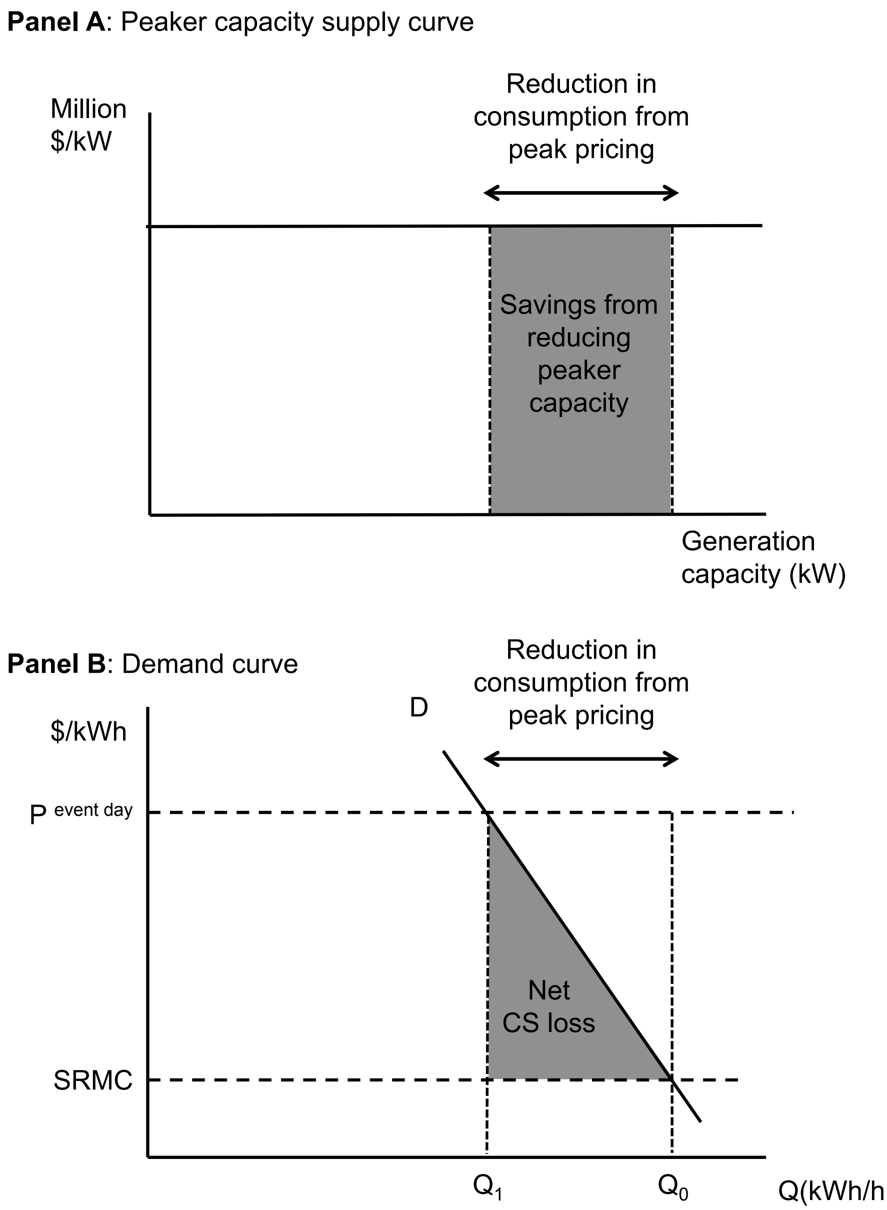
Note. - Each panel on this figure shows the coefficient from seven different regressions estimating the impacts of peak pricing on usage. Each dot represents an individual regression. Panel A shows the results from estimating Equation (1) for inland establishments using bandwidths between 4 and 16 weeks from the September 1, 2011 threshold. Panel B does the same using the RD specification from estimating Equation (3). The dotted lines are the 95% confidence interval. The estimate at eight weeks is the same as the results in Columns (5) and (6) in Table 3.

Figure 8: Effect of Peak Pricing on Inland Establishment Electricity Consumption



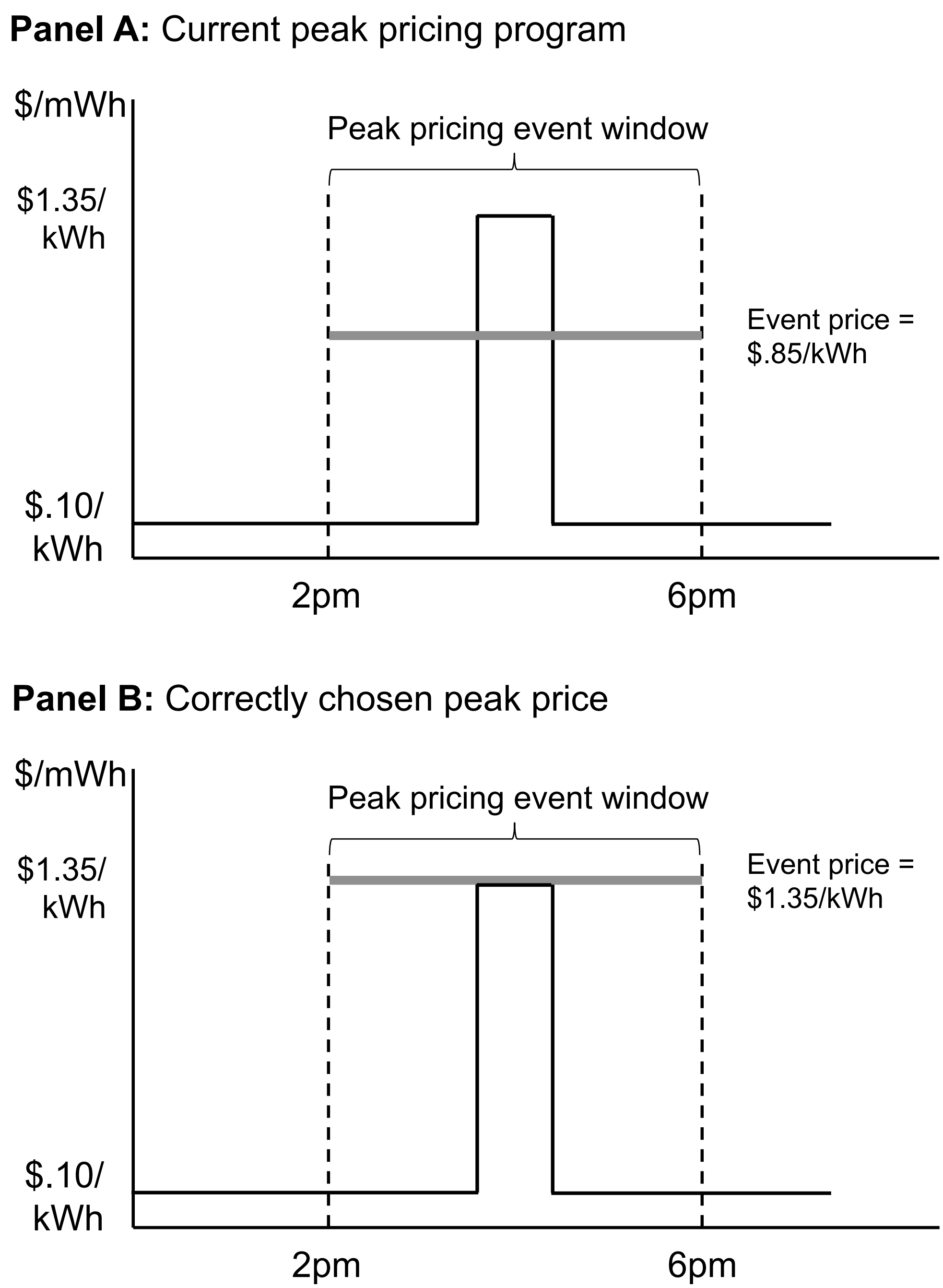
Note. - This figure shows the results of a regression estimating the hourly impacts of peak pricing on event days. Each dot corresponds to an hourly treatment effect comparing treated establishments to the control group. The dotted lines signify the 95% confidence interval. The vertical lines signify the beginning (2:00 pm) and end (6:00 pm) of the peak event window. The regression is estimated on inland establishments using the IV approach. The average impact between 2:00 pm and 6:00 pm reflects the coefficient in Column (5) of Table 3. The results show that establishments begin reducing their electricity usage in the hours before the event window starts. This pattern suggests that some establishments are adjusting their consumption over the whole event day and not just between 2:00 pm and 6:00 pm.

Figure 9: Benefits and Costs of Peak Pricing



Note: - This figure graphically shows the benefits and costs of peak pricing. Panel A shows the capacity supply curve for fossil generation. Reducing peak demand lowers the need for peaker power plants. I assume a constant cost of $1.2 million/MW to build a peaker plant, using California Energy Commission estimates to value the benefits. Using the IV estimate for inland establishments, I find an aggregate reduction of 118 MW, which translates into a reduction of $139 million in capacity costs. Panel B shows the hourly net consumer surplus (CS) loss from calling an event day. The horizontal axis is in kWh per hour (kWh/h), which is equivalent to kW. Short-run marginal production costs (SRMC) are $.102/kWh and reflect the fuel cost at marginal power plants during peak hours. Q_0 is the quantity of electricity consumed during an event hour without peak prices, and Q_1 is the quantity consumed during an event hour with peak prices. I assume a linear demand curve and find that each event day reduces welfare by $209,000. See Section 6.2 for a full discussion of the welfare impacts of peak pricing.

Figure 10: Comparison of Peak Pricing to the First-Best, Real-Time Price



Note. - This figure compares the first-best, real-time price (solid black line) to the peak pricing program on one super-peak event day. The real-time price takes on two values. The low value is $.10/kWh and represents the marginal cost of generation at a low-cost power plant. I assume the price jumps to the high level of $1.35/kWh on three super-peak event days per summer. This high price reflects both the marginal cost and capacity costs on the high demand days. The dashed vertical lines signify the beginning (2:00 pm) and end (6:00 pm) of the peak event window. Panel A shows the current peak pricing program, where the event price is set at $.85/kWh between 2:00 pm and 6:00 pm, which I assume happens on 15 event days per year. Panel B shows the well-targeted version where the event price is set at $1.35/kWh, which I assume happens on eight event days per year. The current program provides 43% of the first-best benefits while the well-targeted program achieves 80%.

Tables

Table 1: Characteristics of Establishments by Peak Pricing Eligibility Status

Variable	Ineligible	Eligible	P value of difference
Summer 2014 avg peak hourly consumption	5.17	5.19	.87
	(3.79)	(3.8)	
Summer 2014 max peak hourly consumption	9.92	10.00	.61
	(6.82)	(6.86)	
Summer 2014 event consumption	218	219	.80
	(165)	(166)	
Summer 2014 non-event consumption	12,412	12,280	.51
	(8,958)	(8,958)	
Summer 2014 electricity expenditure	$563	$557	.54
	(396)	(385)	
Percent of establishments customer facing	.44	.43	.73
	(.5)	(.5)	
Money saved if program run on 2014 usage	-$10	-$12	.16
	(58)	(57)	
Average peak hour temperature (F)	73.24	73.38	.41
	(7.55)	(6.96)	
Establishment count	3,188	4,190	

Notes. - 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. Customer-facing establishments are defined based on North American Industry Classification System codes, as discussed in Section 5.4. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 2: The Effect of Peak Pricing Eligibility on Enrollment (First Stage)

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	FS IV	FS RD	FS IV	FS RD	FS IV	FS RD
Eligible × Post	0.2230***	0.0932**	0.1547***	0.0538	0.3654***	0.2258***
	(0.0064)	(0.0359)	(0.0068)	(0.0361)	(0.0129)	(0.0449)
Establishments	7,435	7,435	5,096	5,096	2,339	2,339
F statistic	406	24	174	15	268	45

Notes. - This table reports regression coefficients from six separate first-stage regressions. 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. "FS IV" and "FS RD" correspond to the first stage of the IV and RD approaches estimated using Equations (2) and (4). All regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors two-way clustered at the establishment and hour-of-sample levels. RD errors 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.

Table 3: The Effect of Peak Pricing on Peak Electricity Consumption (2SLS results)

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	RD	IV	RD	IV	RD
Peak pricing	−0.0695*	−0.2152	0.0084	−0.0584	−0.1441***	−0.2828**
	(0.0412)	(0.2102)	(0.0708)	(0.4227)	(0.0454)	(0.1379)
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

Notes. - This table reports regression coefficients from six separate 2SLS 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, 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 (3). For inland establishments, the IV coefficient corresponds to a 13.4% 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 two-way clustered at the establishment and hour-of-sample levels. RD errors 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.

Table 4: The Effect of Peak Pricing on Peak Electricity Consumption for Inland Establishments: Temperature Interaction

	Inland	
	(1)	(2)
	IV	RD
Peak pricing × Temperature (F)	−0.01120**	−0.03622*
	(0.00450)	(0.02168)
Peak pricing	0.04018	0.18102
	(0.07371)	(0.13676)
Temperature	0.01210***	0.01513***
	(0.00168)	(0.00294)
Temperature squared	−0.00013***	−0.00010
	(0.00004)	(0.00006)
Establishments	2,339	2,339
Event day kWh usage	6.73	6.73
Average temperature	92	92

Notes. - This table reports regression coefficients from two separate 2SLS regressions for inland establishments where treatment is interacted with temperature. The dependent variable in both regressions is the log of establishment hourly kWh consumption. "IV" and "RD" correspond to the instrumental variables and regression discontinuity approaches estimated using Equations (1) and (3). Peak pricing × Temperature (F) is the interaction between the treatment variable and hourly establishment temperature. Temperature has been re-centered at 75 degrees for scaling purposes. The coefficients show that peak pricing impacts are larger on hotter inland event days. In the IV specification, the peak pricing impacts become positive around 79 degrees, which is lower than the temperature for all inland event days. Both regressions include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors two-way clustered at the establishment and hour-of-sample levels. RD errors 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.

Table 5: The Effect of Peak Pricing for Coastal Establishments on Hot Event Days: Alternate Control Day Approach

	Coastal	
	(1)	(2)
	IV	RD
Peak pricing	-0.0783^{**}	-0.0824^{**}
	(0.0361)	(0.0409)
Establishments	2,991	2,991
Event day kWh usage	6.96	6.96
Average temperature	76	76

Notes. - This table reports regression coefficients from two separate 2SLS regressions for coastal establishments. The dependent variable in both 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. To identify the impacts of peak pricing for coastal customers on the hottest event days, I use hot 2015 non-event days instead of 2014 event days as controls. This approach is used because 2014 was a relatively cool summer on the coast, making it a bad control group with which to identify coastal program impacts on hot event days. See Section 5.5 for more details on this approach. The coefficients show the impact of peak pricing on coastal establishment consumption on hot event days 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 (3). Both regressions control for temperature and include hour-of-sample fixed effects and establishment fixed effects. Standard errors are in parentheses. IV errors two-way clustered at the establishment and hour-of-sample levels. RD errors 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.

Table 6: The Effect of Peak Pricing on Peak Electricity Consumption for Inland Establishments: Industry Classification

	All PG&E		Coastal		Inland	
	(1)	(2)	(3)	(4)	(5)	(6)
	Customer facing	Non-customer facing	Customer facing	Non-customer facing	Customer facing	Non-customer facing
Peak pricing	0.0351	-0.1261^{**}	0.0849	-0.0477	-0.0160	-0.1967^{***}
	(0.0555)	(0.0586)	(0.0981)	(0.1021)	(0.0518)	(0.0659)
Establishments	2,889	3,745	2,133	2,468	756	1,277
Event day kWh usage	6.34	5.15	5.66	4.61	8.25	6.19
Average temperature	76	78	71	72	92	92

Notes. - This table reports regression coefficients from six separate 2SLS regressions broken down by industry. 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 use the instrumental variables approach estimated using Equation (1). Establishments are classified as customer-facing or non-customer-facing by their industry classification code, as described in Section 5.4. For inland establishments, the non-customer-facing coefficient corresponds to a 17.9% 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 two-way clustered at the establishment and hour-of-sample levels. RD errors 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.

Table 7: Total Welfare Benefits of Peak Pricing

Scenario	(1) PG&E welfare benefits	(2) IOU welfare benefits	(3) California welfare benefits	(4) National welfare benefits
Small C&I customers	$154	$394	$573	$16,616
All C&I customers	$1,320	$1,940	$2,820	$81,754

Notes. - This table shows the welfare benefits (in millions of 2016 dollars) of the peak pricing program over a 30 year horizon under a number of scenarios. Welfare benefits are calculated using aggregate peak load reduction values informed by empirical estimates. Benefits are primarily due to the reduction in generation capacity necessary to meet peak demand. Costs include the net consumer surplus loss from higher prices on event days. The top left entry shows the estimated savings for the current program in the PG&E service territory. Moving to the right scales this welfare impact for larger regions of the country. The IOU column corresponds to the three major Investor Owned Utilities in California, all of which will implement peak pricing over the next five years. The bottom row extends the peak pricing program to all C&I customers and assumes the same percent reductions for all C&I customers, with adjustments for establishments opting out. Moving both down and to the right, the estimates require more out-of-sample assumptions.

Table 8: Welfare Impacts for 2015 Event Days

Event day	PG&E max load	Annual capacity cost savings (discounted)	Annual net consumer surplus loss (discounted)	NWS day ahead max temperature forecast	Trigger temperature
8/17/2015	19,451	$10,000,000	-$209,000	101	96
6/30/2015	19,320	$0	-$209,000	101	96
7/29/2015	19,248	$0	-$209,000	104	98
8/28/2015	19,233	$0	-$209,000	96	96
9/10/2015	19,230	$0	-$209,000	104	98
9/9/2015	19,017	$0	-$209,000	102	98
7/28/2015	18,403	$0	-$209,000	101	98
8/27/2015	18,328	$0	-$209,000	97	96
6/25/2015	18,114	$0	-$209,000	103	96
9/11/2015	18,019	$0	-$209,000	101	98
6/26/2015	17,950	$0	-$209,000	100	96
7/30/2015	17,750	$0	-$209,000	100	98
7/1/2015	17,734	$0	-$209,000	100	98
8/18/2015	17,372	$0	-$209,000	96	96
6/12/2015	17,275	$0	-$209,000	99	96

Note. - This table shows the two main welfare impacts of the 2015 event days. The annual capacity cost savings shows the benefits of reducing peak load. Annual capacity cost savings includes both the plant construction and operating costs, amortized over the assumed 30 year power plant life. There are non-zero savings numbers only for the super-peak event days of each summer. In 2015, only the highest load day was super-peak. The annual net consumer surplus loss shows the negative welfare consequences of charging higher prices during event hours and is displayed in the same units as capacity cost savings. The values are the same for all event days because the estimate is based on the average impact of peak pricing. NWS day-ahead maximum temperature forecast is the day-ahead temperature used by PG&E to call event days. It is based on the average of five National Weather Service weather stations. When the day-ahead maximum forecast equals or exceeds the trigger temperature, an event day is called.

Table 9: Welfare Impacts of Peak Pricing Under Alternate Scenarios

Scenario	(1) $.85/kWh peak (current price)	(2) $1.35/kWh peak (large C&I peak price)	(3) $1.85/kWh peak (high price)
15 days/summer	$154	$204	$200
101 degree trigger (8 days)	$184	$288	$349
Super-peak days (3 days)	$205	$349	$455

Note. - This is a table that shows the welfare benefits (in millions of 2016 dollars) of the peak pricing program under different program design scenarios. 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 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 reflects the proposed alternate 101 degree trigger for event days, and the bottom row 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.

Table 10: 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)	49%	**80%**	57%
15 event days (current)	**43%**	62%	19%

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 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 five minutes 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 43% of the first-best policy, while the well-targeted program could achieve 80% of the benefits.