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Cloé Garnache[*], Øystein Hernæs,[†] and Anders Gravir Imenes[‡]

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Abstract

Using hourly electricity consumption data for 22,000 households in Norway, we conduct a randomized controlled trial to evaluate the impact of nine critical peak pricing (CPP) events on the grid transmission charge during the winter 2019-2020, with day-ahead notification, on residential electricity consumption. In contrast to most studies, our experimental design relies on an enrollment by default to mitigate sample selection bias. Results show a 13% reduction in electricity consumption during CPP events. We observe little load shifting to non-CPP hours, leading to overall net reductions in electricity consumption, consistent with adjustments in heating-related demand on cold days. Interestingly, electricity consumption reduction is not tied to households having access to real-time consumption, nor is it limited to high-electricity users. We observe, however, that households with electric cars reduce consumption slightly more than other households, with some load shifting to shoulder hours and to the next days.

Keywords: Critical peak pricing, electricity, grid transmission, peak demand, RCT, default enrollment, opt-out

JEL codes: D83, G1, G14, G18, Q54, R30

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1 Introduction

Economists have long advocated for time-varying electricity rates to improve the management of electricity supply generation and retail demand. Large investments in smart metering technology in many parts of the world have recently enabled charging customers for the marginal cost of electricity generation. Different types of time-varying price regimes exist, ranging from simple time-of-use (TOU) rates, which include a few fixed rates (typically peak and off-peak) that vary across periods of the day and/or days of the week, critical peak pricing (CPP) that introduces an infrequent but often dramatic, fixed, and short-lived price rate increase, variable peak pricing (VPP) that allows for variations in the critical price rate increase, to real-time pricing (RTP) that varies according to contemporaneous generation and/or transmission costs.

Yet policy makers and retail electric utilities have largely remained shy of employing time-varying pricing, partly due to concerns about consumers not responding to changes in rates and fear of complaints. In spite of a growing number of recent experimental studies and pilot projects focusing on estimating consumer demand elasticity in specific contexts, uncertainty remains regarding the effect of time-varying rates among the general population. Furthermore, differences in experimental designs such as pricing structure and levels, types of notifications, access to real-time consumption, small sample sizes, and, not least, sample selection bias, make existing results difficult to compare and generalize [Harding and Sexton, 2017].

This paper examines the impact of critical peak pricing (CPP) on residential electricity consumption in Norway, where (1) CPP is implemented with respect to the grid transmission charge, (2) consumers are enrolled by default in a randomized controlled trial (RCT) with an opt-out option, and (3) consumers typically do not have access to real-time electricity consumption. Specifically, using hourly electricity consumption data for about 22,000 households in Norway, we conduct an RCT with CPP on the grid transmission charge during the late afternoons and early evenings on nine selected cold days between December 2019 and April 2020. CPP on the grid transmission charge during a few days in the winter is a relevant policy intervention in Norway. Indeed, the retail price for electricity supply generation already reflects the real-time spot price. However, the grid transmission charge is set to either a winter rate or summer rate, thereby ignoring time-varying congestion on the grid, which may approach transmission capacity constraints on a handful of days every winter. In our experiment, CPP events are announced by text messages on the day prior to each event.

Results show a 13% reduction in electricity consumption during CPP events in the treatment group relative to the control group. Interestingly, electricity consumption reduction is not limited to a small share of households as documented in Reiss and White [2005]. It also does not rely on households having access to real-time consumption information in contrast with Jessoe and Rapson [2014], and is not mostly coming from high-users as shown in Ito et al. [2018] and Burkhardt et al. [2019]. We observe, however, that households with electric cars reduce electricity consumption slightly more than other households, with some load shifting to shoulder hours, consistent with findings in Burkhardt et al. [2019]. Yet, in general, non-electric car households appear to respond to CPP events on cold days with net reductions in electricity consumption, with even some small reductions persisting outside CPP hours and on the next days, differing from the load shifting behavior observed in Bollinger and Hartmann [2015].

These findings are important given the existing challenges associated with balancing a highly variable demand, both throughout the day and across days, with electricity generation supply and transmission congestion along the grid. Generation supply is increasingly volatile due to a growing penetration of renewable energy sources, which has been identified as the culprit for rolling blackouts in California in summer 2020 [Meyer and Waters, 2020]. Furthermore, global electricity demand is predicted to keep rising as a result of rising incomes and increased levels of electrification in developing countries. Electrification has further been promoted globally by policy makers as one of the solutions to mitigating climate change by moving away from fossil fuels, while recent research further suggests that climate change will exacerbate peak demand [Auffhammer et al., 2020]. As a result, current challenges with balancing electricity supply generation and grid transmission with local demand will only become more acute. Policy makers and regulators thus face the challenge of managing future peak demand or addressing future grid capacity constraints with large, likely socially inefficient, investments in expanding the generation and grid capacity.

This paper contributes in three ways to the rapidly growing experimental literature on the effect of time-varying pricing with advanced notice on residential electricity consumption. First, it is the first study to examine a time-varying price for electricity transmission along the grid. Indeed, despite time-varying prices having received much attention as a means to reduce peak load demand when electricity generator capacity binds, they have not been formally examined in the context of peak-load congestion in transmission networks [Wolak, 2011, Harding and Sexton, 2017]. Because of local grid capacity constraints, the marginal costs of electricity delivery to households do not only vary over time but also across regional transmission networks. Therefore, reducing peak demand in a local transmission network close to capacity is considerably more valuable that reducing peak demand in a different transmission network with plenty of spare transmission capacity, all else equal. Grid transmission may be particularly well-suited to CPP as capacity constraints become locally binding on certain days of the year. In particular, grid CPP can offer a long-term, cost-effective solution if the local transmission network serves consumers with a relatively elastic peak demand, e.g., thanks to the the presence of an elastic heating or cooling demand, a high penetration of electric cars with flexible charging needs, or automation technology.

Second, our default enrollment design is critical for minimizing sample selection bias and estimating an accurate response of the effect of time-varying pricing. Most experimental studies rely upon the voluntary recruitment of customers who likely display greater interest in and attention to prices than non-recruited customers. Similarly, the demand response among recruited customers is likely to differ systematically from the demand response of the underlying population of interest, thus limiting the external validity of the results [Joskow and Wolfram, 2012, Harding and Sexton, 2017]. To the best of our knowledge, Fowlie et al. [2017] is the only other study implementing a default enrollment design with opt-out. Their opt-in design leads to a take-up rate of 20%, contrasting with over 90% of the customers remaining in the treatment in their enrollment by default design. The passive customers, i.e., the 70% of customers who would not have opted in but did not opt out when enrolled by default, reduce peak consumption during peak events by only half relative to the customers who actively opted in. Importantly however, the higher participation rate in the enrollment by default design contributes to an aggregate reduction in peak demand that exceeds that achieved by the opt-in group.[1] Furthermore, in the context of an opt-in study design, Andersen et al. [2019] find that demand response estimates are revised downwards by up to four folds when using a censored selection model that accounts for full population participation based on observables. Our default enrollment design enables us to closely approximate the general population's response in Norway.[2]

Third, in contrast with many studies (e.g., Ito et al. [2018], Gillan [2017]), our RCT design does not rely on consumer access to real-time electricity consumption, e.g., via an in-home-display (IHD). We can thus test whether CPP might be readily implementable, albeit conditional on the availability of smart-metering technology. IHD technology enables customers to learn precisely how much electricity each appliance consumes, however, it requires the home installation of a costly piece of technology. The few customers in our sample with IHD prior to the start of the experiment (5%) are randomly assigned among the treatment and control groups. Consumers with IHD reduce peak demand by a further 36% relative to other consumers. This finding is considerably smaller than the 150% additional effect documented in Jessoe and Rapson [2014] and 45% average (up to 76%) effect in Bollinger and Hartmann [2015]. Overall, our results suggest that aggregate reduction in peak demand does not hinge on the availability of IHD.

The paper is organised as follows. The next section provides background on the Norwegian electricity market. Section 3 presents the study design and data. Section 4 outlays the empirical analysis. Section 5 describes and discusses the results. Last, Section 6 concludes.

2 Background on the Norwegian electricity market

Norway has one of the world's highest per capita consumption of electricity, with 23.5 MWh per capita in 2019 – compared with 12.8 MWh in the United States and 6.0 MWh in the EU [IEA, 2020]. Norway faces cold winter temperatures and is highly electrified, with most

[1] Fowlie et al. [2017] show that customer participation choices do not correlate with their expected gains from being in the treatment group. It suggests that customer inattention to the opt-out option drives their passive enrollment decision, rather than switching costs, discounting, or present-biased preferences.

[2] However, our results likely underestimate the treatment effect as the day-ahead notifications do not include the transmission charge and the winter 2019-2020 was an unusually warm winter, limiting the scope for heating-related demand adjustments.

appliances predominantly relying on electricity, including heaters, water heaters, washing machines, and induction stoves. It further has a high penetration of electric vehicles, amounting to 43% of new sales and 9% of the existing registered fleet in 2019 [Norwegian Goverment, 2019]. This high level of electrification makes Norway a particularly interesting case study for policy makers and regulators as it offers a snapshot into what demand may look like in many countries in the near future. If such as a high level of electrification improves peak demand flexibility, it would bode well for demand-side management policies in the long-term.

Consumers in Norway may respond to high electricity prices during peak hours by reducing indoor heating demand and cooking and washing machine use, and adjusting when to charge electric cars. Indeed, studies monitoring appliance-specific electricity use find that home heating and cooling demands are relatively elastic among the demands for electricity services [Reiss and White, 2005, Burkhardt et al., 2019]. Yet, if high electricity prices coincide with mild temperatures, customers may have little room for reducing peak demand through adjusting indoor thermostats. Most drives are quite short and do not require a full battery, however, range anxiety may generate a considerable disutility. Without access to automation, actively curbing peak consumption may reduce welfare, e.g., through the cognitive burden of making adjustment to thermostats or when to charge an electric car, and lead to inelastic demands.

The Norwegian electricity market is deregulated with more than 50 different utilities offering retail electricity contracts to consumers. Grid utilities manage electricity transmission on regional or local networks. They typically have a monopoly over the local grid. Thus, the total electricity price that households face consists of a real-time variable price for retail electricity purchase (the regional spot price augmented by a small fee that accrues to the retailing utility), a rent for the grid connection paid to the grid utility, and a couple of other variable small fees levied by the government. As most electricity in Norway is generated from hydro-power plants, the intra-day variations in spot price are relatively small (Figure A2). However, seasonal variations can be large depending on the hydrological balance. Figure A3 illustrates the variations in the daily spot price in the study region. Possibly because of these relatively small daily variations in spot prices, customers in Norway do not have access to real-time consumption or prices (except through a few small, recent government-sponsored pilot programs), nor do they use automation technologies such as smart chargers for electric cars. The grid rent consists of a fixed fee, which varies across apartments (1,000 NOK per year, or about USD111 using the November 2020 currency rate) and detached or semi-detached houses (2,500 NOK per year), and a variable transmission charge per kWh. This variable transmission charge is set to either a summer tariff or a winter tariff, 0.1813 NOK/kWh and 0.2563 NOK/kWh, respectively, in the years 2017 and 2018. The winter tariff, in effect from November 1st to April 30th, is more expensive due to greater congestion levels on the transmission networks. Grid utilities are mandated to deliver electricity at all times, thus the total capacity of the grid is determined by local peak demands. Peak hours generally occur in the late afternoons and early evenings on cold weekdays in the winter. Yet, as the winter tariff does not vary within days or across days, customers do not currently receive price information signals about grid congestion.

3 Experimental design and data

3.1 Experimental design

We partner with the grid utility Ringerikskraft Nett to design and implement an RCT aimed at studying the effect of time-varying grid pricing on peak electricity consumption. The grid utility serves around 22,000 customers in the municipalities Ringerike and Hole in the Southeast of Norway (one hour drive north of Oslo).

In Norway, electricity transmission levels approach grid capacity constraints a small number of days over the winter, ranging from a few days to a dozen days depending on the intensity of the winter. Grid congestion can be relatively well predicted based on the temperature forecast a day in advance. Furthermore, the literature documents that, absent automation technology, day-ahead notifications perform better at triggering a consumer response than day-of notices, for example because consumers may adjust non-communicating thermostats before leaving for work in the morning [Jessoe and Rapson, 2014, Harding and Sexton, 2017]. This ruled out real-time pricing and time-of-use designs and motivated the choice of a peak pricing design with day-ahead notification.

Furthermore, a growing amount of evidence suggests that, even conditional on access to real-time consumption and price information, consumers are not sensitive to changes in price levels. For example, Jessoe and Rapson [2014] examine price increases from 200% to 600%, while Gillan [2017] investigates price increases from 31% to 1,875%. Limited attention has been proposed as a plausible explanation for consumers' inelastic response to changes in prices [Chetty et al., 2009, Gillan, 2017]. As a result, we choose to focus on a single transmission charge increase, with CPP, rather than exploring VPP.

To select our customer sample, we keep the registered electricity meters satisfying the following criteria. First, we keep meters with total electricity consumption in 2018 between 2,000 kWh and 50,000 kWh so as to exclude potential businesses or malfunctioning meters. Second, we discard customers who did not provide a mobile phone number to send day-ahead SMS notifications. Third, we require meters to be registered with a single customer and customers to be associated with a single meter to ensure the person receiving the notifications lives at the address where the meter is located. At the end of the selection process, our sample consists of 11,712 pre-selected electricity meters.[3] The final sample consists of 11,476 meters.

Using a stratified random sampling design, residential electricity customers were assigned to either the treatment group or the control group. Stratification ensured that the two groups were balanced across households with registered electric car(s) and with real-time consumption IHD. The treatment group consists of 3,833 customers, while the control group consists of 7,643 customers.[4] Non-compliance to the experimental design was observed for 560 customers in the treatment group (14.6%) who contacted the utility to opt-out and, thus, did not face the CPP pricing. Figure A1 illustrates the timing of non-compliance in

[3]Of the 11,712 pre-selected meters, subsequent data on 190 meters were not provided by the utility, for example due to customers moving. An additional 12 meters with values exceeding 50 kWh for a single hour are also dropped. Finally, a further 34 meters are dropped due to having zero electricity consumption in three consecutive weeks.

[4]Our pre-registration plan included a 2×2 design featuring a second treatment arm consisting of an information treatment, with information as similar as possible as that received in the price treatment but without any price change. However, due to the warm winter forecast in Norway in 2019-2020 and low congestion levels anticipated on the grid, the grid utility canceled this arm of the treatment prior to the start of the RCT as it seemed unethical to ask customers to reduce peak demand to alleviate pressure on the grid. Customers originally assigned to the information treatment arm were pooled with the control group. Because of the warm weather, the grid utility further decided to skip the first treatment event planned for November 2019, resulting in nine events instead of the ten originally planned. The average temperature in the study area during winter 2019-2020 (December through April) was 2.3°C, which is 2.5°C warmer than in winter 2018-2019 and 3.9°C warmer than in winter 2017-2018.

the treatment group – 70% of those 560 customers were non-compliant prior to the first CPP event. Another nine customers from the control group (0.1%) requested to participate in the CPP treatment and, thus, received CPP pricing.[5] However, these non-compliers are included in the analysis according to their original assignment to maintain the randomization. Therefore, we estimate the intention-to-treat effect.

The CPP treatment raises the winter grid tariff from 0.24 NOK/kWh to 10 NOK/kWh from 16h to 22h on nine CPP weekdays in the period December 2019 to April 2020 (two CPP days per month from December to March and one CPP day in April). CPP weekdays were called by the grid utility a day in advance as informed by high transmission congestion forecasts related to cold temperatures.[6] The CPP program was designed to be revenue-neutral for the grid utility, based on electricity consumption in the prior year. Consequently, the winter grid tariff for non-CPP hours was reduced to 0.05 NOK/kWh in the treatment group so as to offset the effect of the 10 NOK/kWh CPP pricing for the average customer, assuming no adjustment in consumption.

Every customer in the treatment group was mailed a letter in late November about the overall goal of the CPP program to reduce peak demand grid congestion and avoid future costly investments in expanding grid capacity. The letter included the number of CPP days and CPP hours, and information on how to opt out. Enclosed to the letter was a two-sided brochure featuring on one side the CPP transmission charge of 10 NOK/kWh with an example of cost calculation for running an appliance during CPP hours, and tips on reducing peak electricity demand on the other side. The letter and brochure are shown in Appendix C.2. On December 6th, customers were emailed a shorter version of the letter they received in the mail, notifying them that the first CPP event would occur the following week, and a reminder on how to opt out (Appendix C.3). The email also included a link to the online brochure that they received in the mail. Customers in the treatment group received an SMS on the day prior to a peak event, between 14h00 and 15h00, with a second SMS reminder sent on the day of an event for the first five events. An overview of the timing of the CPP events

[5] A utility representative gave an interview about the CPP program in the local newspaper, leading to a few customers requesting to participate in the CPP treatment.

[6] By choice, Mondays were never called by the utility as it would have required calling employees to work overtime on a Sunday to prepare for the Monday event. In practice, most CPP weekdays happened on Tuesdays and Thursdays, with one Wednesday drawn. No Friday ended up being called.

and communication with the customers is depicted in Figure C1. The content of the SMSs is shown in Appendix C.4. Importantly, note that, per decision of the grid utility who feared customer complaints, only the brochure featured the CPP transmission charge level, but not any of the SMSs nor the letters. We do not know how many customers read the brochure in the mail or online. Of those who read the brochure, we cannot say which fraction remembered the CPP transmission charge level when making electricity consumption decisions during the nine CPP events. Therefore, it is likely that our treatment effect is underestimated.

To examine whether peak demand response to CPP can be made more effective, we implement a secondary treatment using social comparisons. Experimental studies have found mixed effects of nudges and social norms on peak demand consumption [Carlsson et al., Forthcoming]. In general, the effect is marginal, typically less than 3%, however, the cost of such interventions is also usually relatively small [Gillan, 2017, Ito et al., 2018, Andersen et al., 2019]. Our secondary treatment design consists of including social comparisons to the CPP treatment in the last two CPP events. Specifically, half of the CPP treatment group receives information on their electricity consumption during the previous CPP event and during the same hours on the day prior to that CPP event, plus information on how much the rest of the treatment group changed consumption between the same two time periods. The other half of the CPP treatment group receives the same CPP event notification as usual.[7]

3.2 Data

Using Ringerikskraft Nett's high-frequency smart meter data on household electricity consumption in the pre-treatment period and during the experiment, we construct our main dependent variable as the natural logarithm of hourly electricity consumption in and outside

[7]The grid utility implemented several notable deviations from the pre-registration plan due to unforeseen technical challenges with computing the change in one's own consumption and sending out the messages. First, the grid utility decided to postpone the secondary treatment, which was originally planned for the last four events. Second, it simplified the social comparison information by not including the change in one's own consumption, but only the levels, making the social comparison with the rest of the group's change in consumption less straightforward (see SMS in Appendix C.4). Third, the second half of the CPP treatment group was supposed to receive feedback information on their own change in electricity consumption during the last CPP event, but *without* the social comparison, in order to isolate the effect of social comparisons from the simple information feedback on one's own consumption.

of the treatment window (16h-22h). The temperature variable is constructed using the hourly temperature at the Hønefoss weather station and, thus, does not vary across households. Using customers' name and address, we match households with the electric vehicle ownership registration database from the Norwegian Public Roads Administration (Vegdirektoratet). Per mid-September 2019, 1,200 inhabitants in the municipalities Ringerike and Hole were registered as the owner of at least one electric car. 611 of these were merged by first and last names to the electricity meter. To include cases where the car and meter are registered to different members in the household, a further 103 were merged by last name and address. Finally, 107 (unique) matches were made using the address only, but we deemed the quality of those matches too uncertain, and do not include them in the analysis. Table 1 includes data on the 714 electric car records that are matched on full name or last name and address.

Last, although every customer in Norway is equipped with a smart meter, households typically learn about their electricity consumption via their monthly bill. The most timely electricity consumption is available only up to the previous day by logging onto an app or into a secure government website. There is thus an apparent disconnect between facing real-time retail prices, while not having information on real-time retail prices and consumption. Several small, recent, ongoing government-sponsored grant programs examine the effect of IHD on consumption. One of these programs involve the customers served by our grid utility (https://www.energipilot.no/). The program randomly made free IHD offers to 1,865 customers in 2017. Of those, 738 customers accepted the offer, received the device, and installed it – of whom 595 remained at the end of the pre-selection process for our CPP experiment. We randomize those customers, resulting in 201 customers with IHD assigned to the treatment group and 394 to the control group.[8]

Descriptive statistics are shown in Table 1. Electricity consumption and observables driving electricity consumption and the response to the treatment appear well balanced between the treatment group and control group in the pre-treatment period. Therefore, the table provides support for the randomization of treatment across our sample.

[8] In summer 2019, a survey was distributed to all customers who had accepted the IHD offer and received the device, albeit not necessarily installed it. Summary statistics are shown in Table A1.

Table 1 Descriptive statistics for the estimation sample in the pre-treatment period (January 1 – November 30 2019).

	Treatment		Control	
	Mean	SD	Mean	SD
Electricity consumption (kWh)	1.81	(1.54)	1.81	(1.53)
00h-16h	1.73	(1.47)	1.72	(1.47)
16h-22h	2.02	(1.67)	2.02	(1.67)
22h-00h	1.88	(1.57)	1.88	(1.56)
Electric car household (0/1)	0.06	(0.25)	0.06	(0.24)
Real-time in-home display (0/1)	0.05	(0.22)	0.05	(0.22)
Temperature (°C)	6.86	(8.52)	6.86	(8.52)
Non-complier (0/1)	0.14	(0.35)	0.00	(0.03)
N	3,833		7,643	

4 Empirical strategy

4.1 Empirical models

The main hypothesis is that the CPP treatment will decrease peak electricity consumption. Important questions we aim to answer is which consumer groups respond to the treatment, how does the treatment leads to a reduction in electricity consumption during peak hours, i.e., elicit whether this decrease represents a net reduction in electricity use or load shifting to non-peak hours or other days, and whether we detect habituation to the treatment with declining effects over time.

Our basic model specification is shown in equation (1):

$$\begin{aligned} E_{it} &= \beta_1 Treat_i * Peak_d * Day_d + \gamma_1 Treat_i * NPeak_d * Day_d \\ &+\beta_2 Treat_i * Peak_d * Post_d + \gamma_2 Treat_i * NPeak_d * Post_d \\ &+\delta f(temp)_t + \phi X_{it} + \epsilon_{it}. \end{aligned} \tag{1}$$

The variable E_{it} indicates household i's log of electricity use in kWh in each hour t. Each day d is divided into two time periods: non-peak hours, namely 00-16h and 22-24h ($NPeak_d$), and peak hours 16-22h ($Peak_d$). $Treat_i$ denotes treatment group status (0 or 1). Day_d is a dummy variable that takes the value 1 on days when a CPP event occurs and 0 otherwise. $Post_d$ denotes the two days following a CPP event. The variable $temp$

represents hourly temperature in degree Celsius in the town of Hønefoss. Our measure of temperature, $f(temp)_t$, consists of a polynomial of degree three in hourly temperature and linear measures of the average temperature the preceding 24, 48 and 72 hours. The vector $\mathbf{X}_{it}$ includes household fixed effects, time of day fixed effects (peak or non-peak hours) and date fixed effects to control for demand shocks that affect our sample.

Households owning at least one electric car may respond differently to treatment relative to non-electric car households due to a larger electric consumption to start with and greater flexibility regarding when to charge the car. Thus, to allow for treatment heterogeneity across households with or without electric cars, we interact all the terms in equation (1), except $\mathbf{X}_{it}$ and $f(temp)_t$, with a dummy variable, $Ecar$, indicating whether the household owns an electric car.

To examine more precisely whether households shift electricity consumption to pre- and post-CPP hours, we refine equation (1) to include shoulder hours.[9] Our preferred specification is depicted in equation (2):

$$\begin{aligned} E_{it} &= \beta_1 Treat_i \times Peak_d \times Day_d + \gamma_1 Treat_i \times NPeak_d \times Day_d \\ &+\beta_2 Treat_i \times Peak_d \times Post_d + \gamma_2 Treat_i \times NPeak_d \times Post_d \\ &+\lambda_1 Shld_d + \lambda_2 Treat_i \times Shld_d \times Day_d + \delta f(temp)_t + \phi X_{it} + \epsilon_{it}. \end{aligned} \tag{2}$$

The shoulder hours in each day are defined as the two hours pre- and post-CPP hours, i.e., 14-16h and 22-24h, while the non-peak hours are now redefined as 00-14h. Time of day fixed effects now consist of peak, non-peak, or shoulder hours to control more precisely for changes in daily electricity consumption patterns.

4.2 Graphical inspection

Next, we provide visual evidence of the effect of the CPP treatment on electricity consumption. The following figures offer (1) an overview of electricity consumption over the five months of the experiment, (2) a focus on each CPP event, and (3) an inspection of the differential response of households with or without electric cars.

[9] Equation (2) contained a typo in the pre-registration plan that said that the shoulder hours indicator was to interact with the indicator for the post-CPP days. This should have been the indicator for the CPP day. The pre-registration plan was amended accordingly.

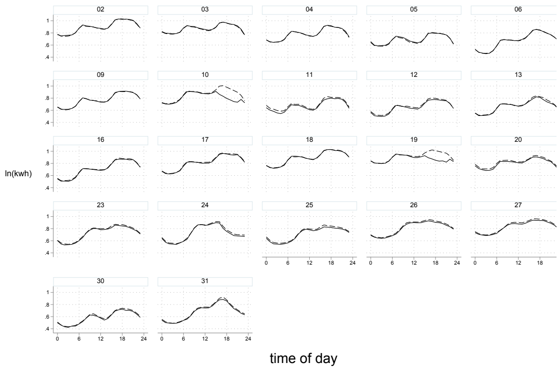
Figure 1 depicts the log of electricity consumption for the treatment and control groups for all weekdays in the period December 2019 – April 2020, which includes all nine CPP events.[10] Days with CPP are easily recognizable from the difference in consumption patterns between the treatment and control groups, while no differences between the two groups are noticeable on non-CPP days.

Figure 2 shows the log of electricity consumption on the nine CPP events, including on the day prior and the day after the CPP event. The treatment effect appears concentrated on the six CPP hours on the day of the CPP event, with no evidence of load shifting to non-CPP hours or non-CPP days. The treatment effect possibly declines over the last CPP event. This seems to be correlated with warmer temperatures (see Figure A3), which may trigger lower heating-related demands and leave less scope for adjustments.

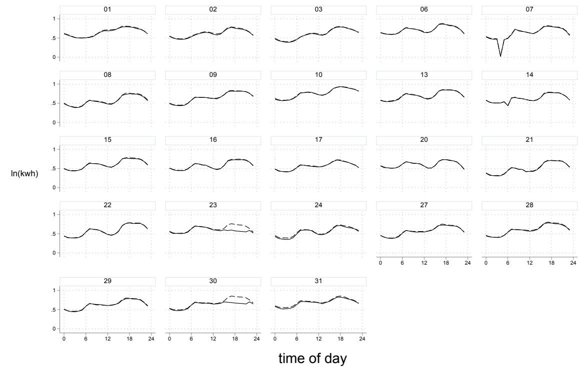
Figure 3 illustrates the log of electricity consumption for each CPP event, while separating the response of households with electric cars from that of households without. Although households with electric cars have a higher electricity consumption, the consumption pattern between electric car and non-electric car households is relatively similar across the nine days with CPP. Furthermore, the solid and dashed lines for the treatment and control groups, respectively, follow each other closely, except during CPP events during which they diverge sharply. Households with electric cars appear to respond slightly more to CPP events than households without electric cars. This is not surprising as electric cars offer one additional margin of adjustment on which consumers can act upon. Therefore, even though smart chargers are not common in Norway, households appear to exploit this margin of adjustment and actively forego or postpone charging their car during CPP events.

Figure 4 shows the log of electricity consumption on the last two CPP events for the CPP treatment group. Half of the treatment group received feedback information on their own consumption during the previous CPP event and on the day prior to that CPP event during peak hours, with a social comparison with the relative change in consumption between these two time periods in the rest of the treatment group. The other half of the treatment group received the regular CPP event notification. Similarly to Figure 3, the response to treatment

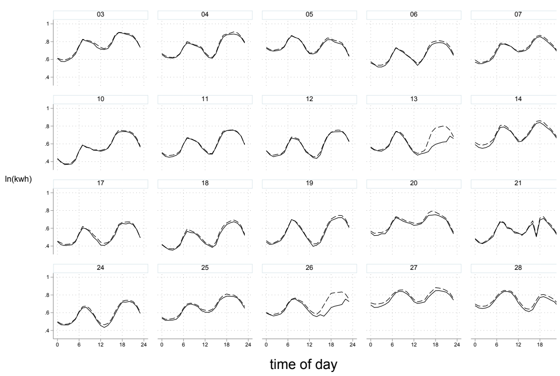
[10]Short, local power outages (e.g., due to trees falling on power lines) took place on January 7th and 14th and February 21st. These outages affected treatment and control groups alike and always occurred outside CPP events.



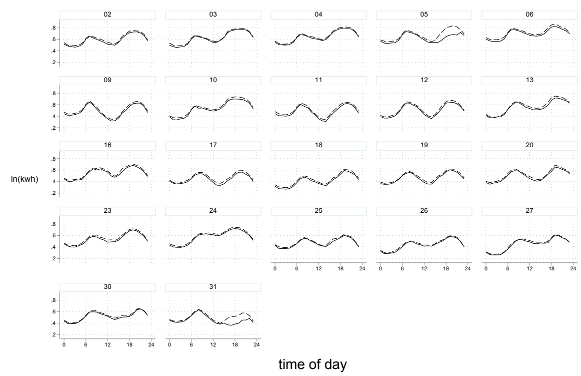
(a)



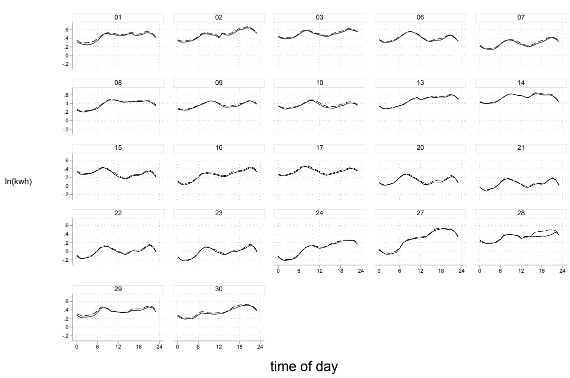
(b)



(c)



(d)



(e)

Figure 1 Log of hourly electricity consumption. Every frame depicts a day. All days during the five months of the experiment, from December 2019 (panel (a)) to April 2020 (panel (e)) are shown, with weekends excepted. Solid line depicts the treatment group; dashed line the control group.

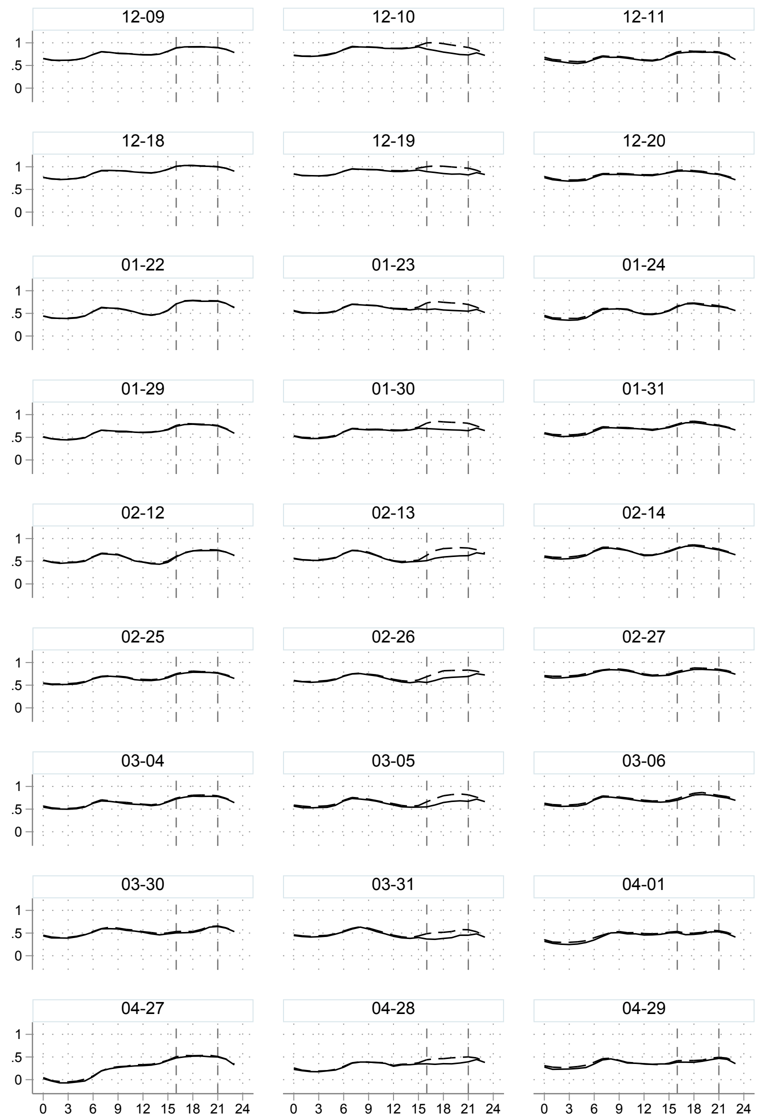


Figure 2 Log of hourly electricity consumption on the nine CPP days (middle panels), including one day prior (left panels) and one day post CPP event (right panels). Each CPP event is depicted on a different row, with the 1st CPP event on December 10th on the top row and the 9th CPP event on April 28th on the bottom row. The nine events occurred on: 1) 10-12-2019, 2) 19-12-2019, 3) 23-01-2020, 4) 30-01-2020, 5) 13-02-2020, 6) 26-02-2020, 7) 05-03-2020, 8) 31-03-2020, 9) 28-04-2020. Solid line depicts the treatment group; dashed line the control group. The CPP hours (16h-22h) are marked with vertical dashed lines.

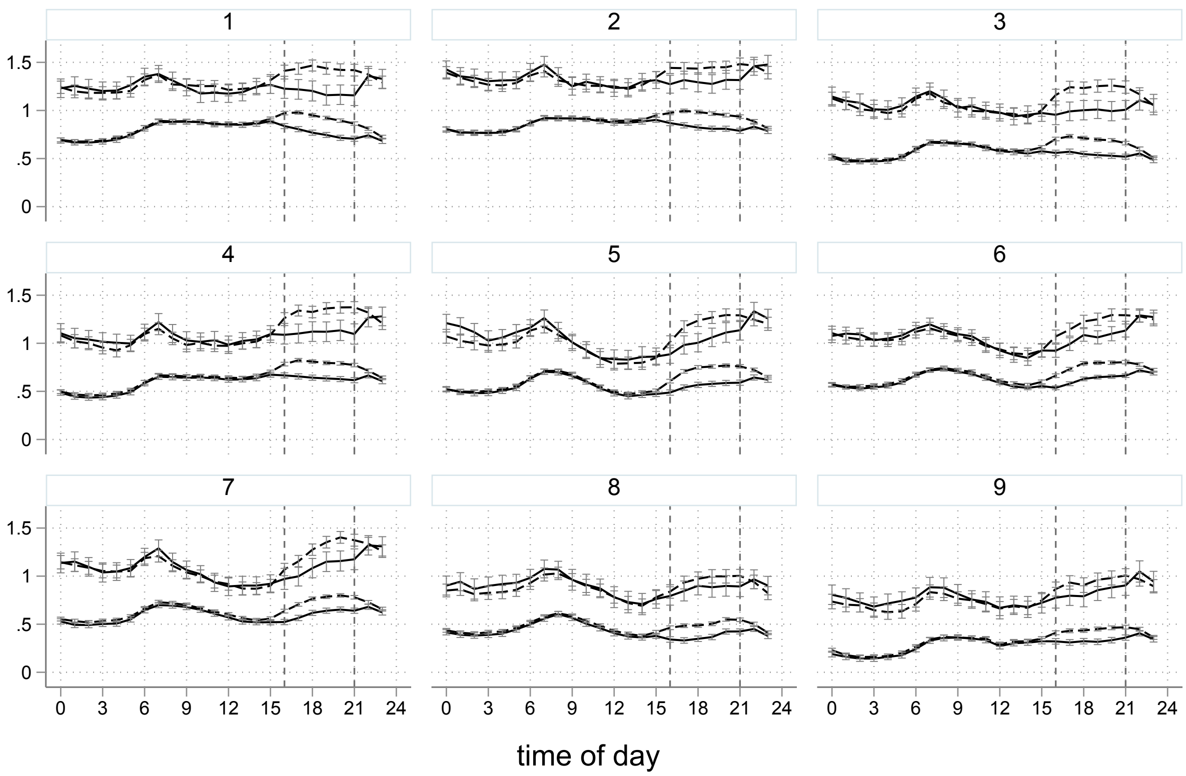


Figure 3 Log of hourly electricity consumption on the nine CPP days, differentiating the response to treatment across households with (top lines) and without electric cars (bottom lines). Vertical bars denote 95-% confidence intervals. Each panel depicts a day with a CPP event. The nine events occurred on: 1) 10-12-2019, 2) 19-12-2019, 3) 23-01-2020, 4) 30-01-2020, 5) 13-02-2020, 6) 26-02-2020, 7) 05-03-2020, 8) 31-03-2020, 9) 28-04-2020. The solid lines depict the treatment group; dashed lines the control group. The CPP hours (16h-22h) are marked with vertical dashed lines.

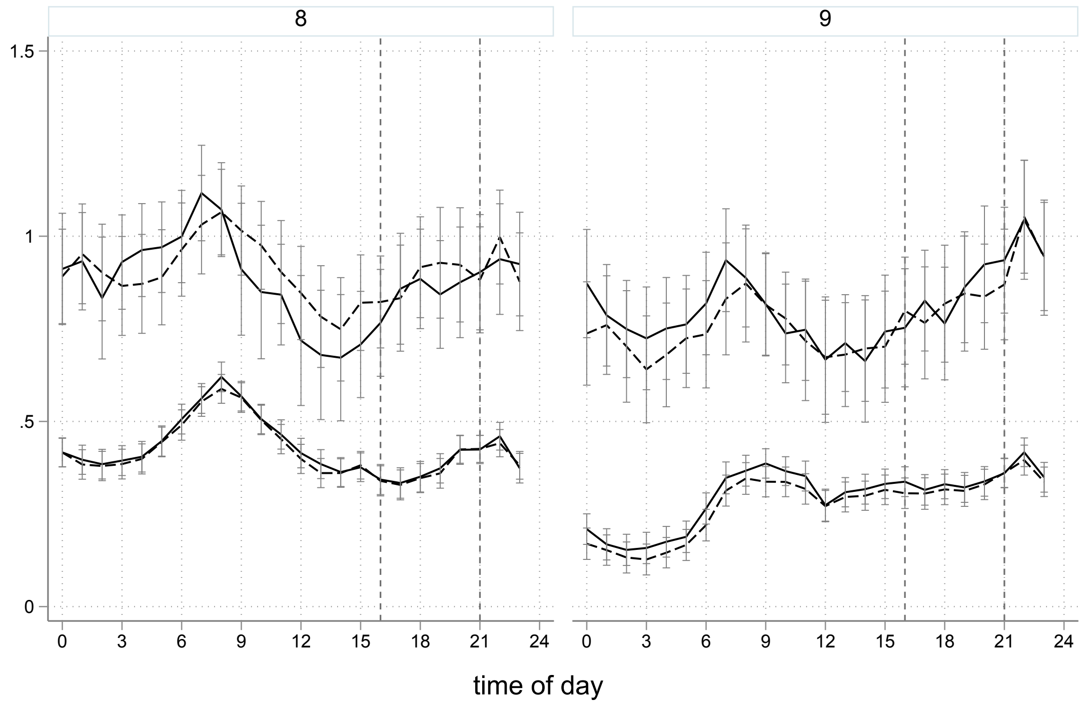


Figure 4 Log of hourly electricity consumption on the last two CPP days, which feature social comparisons with feedback on one's own consumption during the prior CPP event and on the day prior, differentiating the response to treatment across households with (top lines) and without electric cars (bottom lines). Vertical bars denote 95-% confidence intervals. Each panel depicts a day with a CPP event. The secondary treatment was implemented during the 8th and 9th CPP events, which occurred on: 31-03-2020 and 28-04-2020. The solid lines depict the half of the treatment group that received one's own consumption feedback and social comparison; dashed lines the other half of the treatment group that received the regular CPP event notification. Note that data are not shown for the control group. The CPP hours (16h-22h) are marked with vertical dashed lines.

of households with electric cars is separated from that of non-electric car households – and their consumption remains the highest. Figure 4 fails to show a clear effect of the feedback with social comparison treatment relative to the regular CPP event notification. The absence of a visible effect is noticeable for both households with and without electric cars. However, it is important to keep in mind that the last two events (on March 31 and April 28) occurred on warmer, spring days (Figure A3), during which the heating-related demand is lower and may not offer much scope for adjustment.

5 Results

5.1 Response to CPP treatment for all consumers

In this section, we show empirically the effect of the grid CPP treatment on household peak electricity consumption. Regression results with household fixed effects are shown in Table 2 and without household fixed effects in Table B1. In each table, results for equation (1), both without and with temperature controls, are shown in columns (1) and (2), while results for the model allowing for treatment heterogeneity across households with or without electric cars are depicted in column (3). Results for equation (2) with shoulder hours, both without and with electric car treatment heterogeneity, are shown in columns (4) and (5).

For each specification in Table 2, a CPP event is associated with a reduction in peak electricity consumption among treatment households of 0.14 log points (or 13%) relative to control households ($Treat \times Peak \times Day$). Taking into account variations in the spot price over the nine CPP events (from 0.14 NOK/kWh to 0.59 NOK/kWh), the total electricity price increase between the treatment and control groups ranged from 892% to 1,498%, with mean 1,242%. This is equivalent to an average price elasticity of -0.015. Starting with the basic model in equation (1), without or with temperature controls (columns (1) and (2), respectively), estimates indicate a slightly lower electricity consumption during the two days post CPP, in particular during peak hours. There is thus no sign of load shifting to the next days but, rather, evidence of a small persistence effect on the two days following a CPP event. This persistence effect is consistent with households responding to a CPP event by adjusting the setting of programmable thermostats during peak hours and not returning the thermostat to the pre-CPP event setting for some days.

Treatment heterogeneity across households with or without electric cars is shown in column (3). Households with electric cars display higher electricity consumption during peak hours than non-electric car households (0.059 log points or 5.7%; p-value<0.01). However, they reduce consumption during CPP events with a few percentage points more than treated households without electric cars (0.057 log points or 5.5%; p-value<0.05). Interestingly, electric car households substantially shift their consumption to non-peak hours both on the CPP

Table 2 Effect of CPP events on log of hourly electricity consumption. (1) and (2): Equation (1) both without and with temperature controls. (3): Equation (1) with treatment heterogeneity across households with or without electric cars. (4) and (5): Equation (2) with shoulder hours, both without and with electric car treatment heterogeneity. All specifications include household, date, and time of day (peak or non-peak) fixed effects. In columns (4) and (5), time of day fixed effects consist of peak, non-peak, or shoulder time. (The mean log electricity consumption (*ymean*) is 0.586.)

	(1)	(2)	(3)	(4)	(5)
$Treat \times Peak \times Day$	-0.140***	-0.139***	-0.136***	-0.139***	-0.135***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Treat \times NPeak \times Day$	-0.002	-0.003	-0.004**	0.007***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Treat \times Peak \times Post$	-0.026***	-0.018***	-0.017***	-0.018***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Treat \times NPeak \times Post$	-0.003*	-0.005***	-0.006***	-0.005***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Peak$	0.138***	0.143***	0.140***	0.161***	0.157***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
$Treat \times Peak \times Day \times Ecar$			-0.057**		-0.057**
			(0.022)		(0.022)
$Treat \times NPeak \times Day \times Ecar$			0.020***		0.020**
			(0.007)		(0.008)
$Treat \times Peak \times Post \times Ecar$			-0.021**		-0.021**
			(0.009)		(0.009)
$Treat \times NPeak \times Post \times Ecar$			0.014**		0.014**
			(0.006)		(0.006)
$Peak \times Ecar$			0.059***		0.063***
			(0.006)		(0.007)
$Treat \times Shld \times Day$				-0.042***	-0.042***
				(0.003)	(0.003)
$Shld$				0.065***	0.064***
				(0.001)	(0.001)
$Treat \times Shld \times Day \times Ecar$					0.003
					(0.012)
$Shld \times Ecar$					0.017**
					(0.005)
temp	No	Yes	Yes	Yes	Yes
R^2	0.727	0.727	0.727	0.728	0.728
N	42,323,924	42,323,924	42,323,924	42,323,924	42,323,924

Note: Robust clustered standard errors at the household level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

day and on post-CPP days ($Treat \times NPeak \times Day \times Ecar$ and $Treat \times NPeak \times Post \times Ecar$). Consumption remains somewhat lower during peak hours on post-CPP days ($Treat \times Peak \times Post \times Ecar$). Together these findings suggest persistent adjustments in the car charging timing and a potential for habit formation.

Load shifting to shoulder hours is shown in columns (4) and (5), without and with allowing for heterogeneity across electric car households, respectively. Results in column (4) suggest that the reduction in electricity consumption outside the peak hours of a CPP day largely took place in the shoulder hours, with a reduction of 0.042 log points or 4.1% for the treatment group relative to the control group. The reduction in electricity consumption in the shoulder hours is not significantly different when examining the response of electric car households ($Treat \times Shld \times Day \times Ecar$; column (5)), despite them having a slightly higher electricity consumption during those hours of the day.

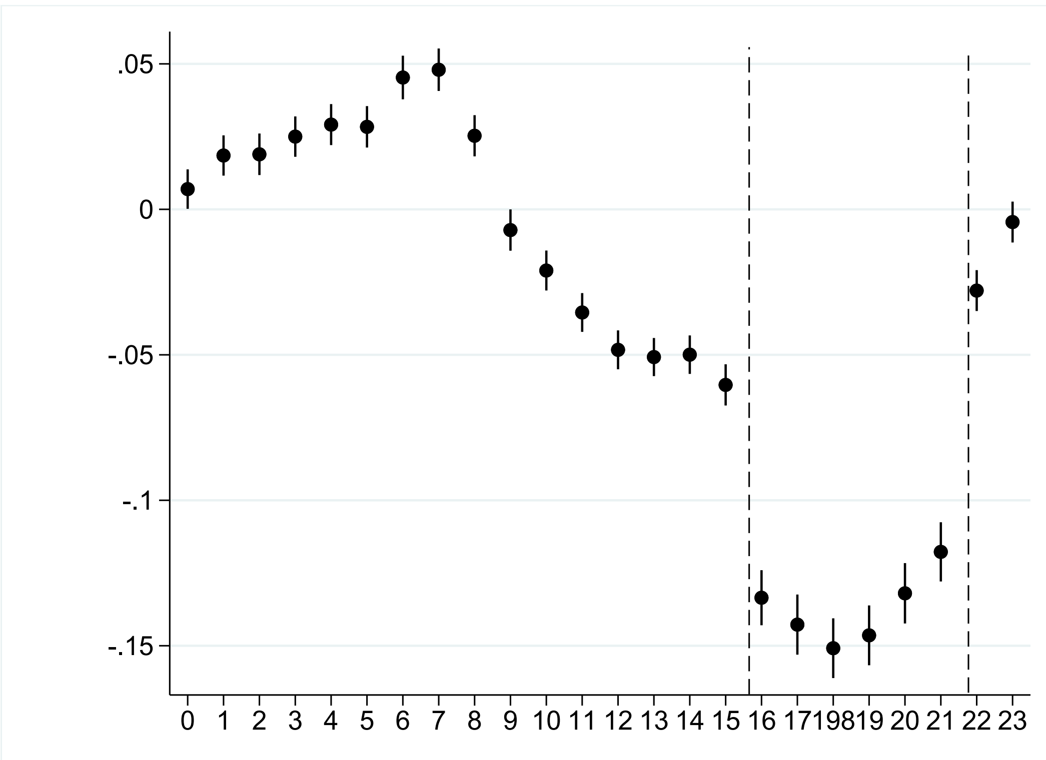


Figure 5 Effect of CPP events on log of hourly electricity consumption for each hour of a CPP day. Hourly effects, depicted with 95%-confidence intervals, are estimated by modifying equation (1) to include $Treat \times Hour \times Day$, where $Hour$ denotes each hour from 00h to 23h. Electric car treatment heterogeneity and household and date fixed effects included.

To examine more precisely how CPP affects the behavior of the treatment group relative to the control group throughout the day, we show the effect of CPP on household electricity consumption for each hour of a CPP day in Figure 5. In addition to the sharp peak demand reduction observed during the CPP hours, 16h-22h, reductions in demand are already noticeable from 9h on and last until 23h, possibly capturing the effect of households manually adjusting heating thermostats before leaving to work. The most pronounced reduction occurs in the afternoon hours, 12h-15h, prior to the start of the CPP event (about 0.05 log points or 5%). Interestingly, we observe a small increase in consumption during the night and early morning hours of a CPP day, from 1h until 8h, indicating a small amount of load shifting, consistent with the sign of $Treat \times NPeak \times Day$ in Table 2, column (5), which separates shoulder hours from other non-peak hours. However, the net overall effect during the day, i.e., encompassing non-peak and shoulder hours, remains negative ($Treat \times NPeak \times Day$ in Table 2; column (3)).

5.2 Response to CPP treatment across consumer groups

To better understand who the households that respond to treatment are, we now re-estimate for different consumer groups our preferred specification, i.e., equation (2) with household fixed effects and allowing for heterogeneity among households with or without electric cars. Results are shown in Table 3 for consumers with or without IHD, and for consumer type as defined by their electricity consumption quartile in the pre-treatment period (January – November 2019).

Table 3 shows that all consumer groups reduce electricity consumption during CPP events, with an effect ranging from -0.11 to -0.18 log points or -10% to -16%. This finding is relevant to policy makers and contrasts with results from prior studies that suggest that peak pricing without access to real-time consumption information has a considerably weaker effect [Jessoe and Rapson, 2014], or that most of the response comes from high-use consumers (e.g., Reiss and White [2005]). In addition, we do not find strong evidence that electric car households in any of the groups considered drive the response to treatment, which is in contrast with findings in Burkhardt et al. [2019]. Furthermore, rather than shifting their electricity demand to shoulder hours or onto the next two days, most groups have a tendency to also reduce their electricity consumption, in particular during shoulder hours and the peak

Table 3 Effect of CPP on log of hourly electricity consumption for consumer groups based on real-time IHD (columns (1) and (2)), and on pre-treatment electricity consumption quartiles (columns (3) and (6)). All specifications use equation (2) with shoulder hours and electric car treatment heterogeneity. All specifications include household, date, and time of day (peak, non-peak, or shoulder hours) fixed effects.

	IHD		Consumption quartile			
	With	Without	1^{st}	2^{nd}	3^{rd}	4^{th}
	(1)	(2)	(3)	(4)	(5)	(6)
$T \times P \times Day$	-0.181***	-0.133***	-0.107***	-0.120***	-0.167***	-0.148***
	(0.023)	(0.005)	(0.005)	(0.008)	(0.010)	(0.010)
$T \times NP \times Day$	0.003	0.006**	0.006	0.006	0.006*	0.003
	(0.008)	(0.002)	(0.006)	(0.004)	(0.004)	(0.003)
$T \times P \times Post$	-0.010	-0.018***	-0.016***	-0.007	-0.026***	-0.018***
	(0.009)	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)
$T \times NP \times Post$	-0.003	-0.008***	-0.007	-0.006**	-0.008***	-0.003
	(0.007)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
P	0.162***	0.157***	0.226***	0.132***	0.134***	0.132***
	(0.006)	(0.002)	(0.005)	(0.003)	(0.003)	(0.002)
$T \times P \times Day \times Ecar$	-0.142**	-0.042*	-0.059	-0.061	-0.023	-0.053
	(0.068)	(0.022)	(0.048)	(0.056)	(0.041)	(0.032)
$T \times NP \times Day \times Ecar$	0.020	0.019**	-0.044	0.015	0.029*	0.015
	(0.018)	(0.009)	(0.039)	(0.019)	(0.015)	(0.011)
$T \times P \times Post \times Ecar$	-0.023	-0.021**	-0.149***	-0.067**	0.015	-0.011
	(0.025)	(0.009)	(0.035)	(0.028)	(0.018)	(0.011)
$T \times NP \times Post \times Ecar$	0.018	0.017***	-0.043	0.014	0.028**	0.008
	(0.013)	(0.006)	(0.038)	(0.016)	(0.011)	(0.006)
$P \times Ecar$	0.040**	0.066***	0.143***	0.099***	0.098***	0.068***
	(0.018)	(0.008)	(0.038)	(0.021)	(0.014)	(0.008)
$T \times Shld \times Day$	-0.033***	-0.042***	-0.039***	-0.042***	-0.050***	-0.042***
	(0.011)	(0.003)	(0.007)	(0.005)	(0.004)	(0.004)
$Shld$	0.052***	0.065***	0.110***	0.049***	0.047***	0.047***
	(0.005)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
$T \times Shld \times Day \times Ecar$	-0.026	0.007	-0.043	0.002	0.018	0.009
	(0.034)	(0.012)	(0.060)	(0.034)	(0.029)	(0.013)
$Shld \times Ecar$	0.017	0.018***	0.067***	0.062***	0.030***	0.022***
	(0.014)	(0.006)	(0.025)	(0.015)	(0.010)	(0.006)
temp	Yes	Yes	Yes	Yes	Yes	Yes
ymean	0.896	0.569	-0.348	0.508	0.877	1.305
R^2	0.615	0.727	0.541	0.322	0.347	0.444
N	2,190,913	40,133,534	10,562,665	10,582,188	10,589,902	10,583,005

Note: Robust clustered standard errors at the household level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

hours of the next two days, i.e., 16h to 22h. This may suggest adjustments in the setting of programmable or non-programmable thermostats or water heater with some inertia for returning to the original setting.

Columns (1) and (2) in Table 3 illustrate the effect of CPP events on consumers conditional on whether or not they had installed an IHD prior to the experiment to monitor their real-time consumption. Without IHD, households interested in their recent consumption may log onto an app or a secure government website and observe their consumption for up to the previous day. Notably, consumers who installed an IHD have on average a higher electricity consumption (y_{mean} = 0.896 vs. y_{mean} = 0.569, or 2.45 kWh vs. 1.77 kWh), possibly motivating them in the first place to monitor their consumption and save on their electricity bill. Households with IHD display a reduction in consumption of 0.18 log points or 16%, compared to 0.13 log points or 12% for the group without IHD – amounting to a 33% difference. When households with IHD also own electric cars, they dramatically reduce their consumption during CPP events, i.e., by another 0.14 log points or 13% ($T \times P \times Day \times Ecar$; p-value<0.05).

Columns (3) to (6) in Table 3 show the effect of CPP events on consumer groups conditional on their pre-treatment electricity consumption. The two lowest consumption quartiles reduce electricity consumption by 0.11 to 0.12 log points, or 10% to 11%, in response to the treatment, which is slightly less compared to the 0.15 to 0.17 log points, or 14% to 16%, for the top two quartiles.

5.3 Habituation to CPP treatment (and potential Covid-19 effect)

In Appendix B Table B2, we examine whether consumers become habituated to CPP events and, thus, less responsive over time. We do not find evidence of such trend with reductions during CPP events ranging from 0.13 to 0.17 log points, or 12% to 16%, with the exception of the last CPP event on April 28th that occurred on a warm spring day, with a reduction of only 0.4 log points or 4%. The absence of a declining treatment response in the event by event analysis suggests that such CPP interventions could be relevant for long-term grid transmission congestion and peak demand management.

Furthermore, the last two CPP events coincide with the Norwegian Covid-19 lockdown, which started on March 12th 2020 and lasted, in its strictest form, until April 28th 2020. Schools and gyms were closed, work from home was mandated whenever possible, and strict restrictions on social gatherings and social life were implemented. Date fixed effects in all specifications control for the component of the shock that affects all households. Yet, it is possible that household behavior and response to treatment during the lockdown changed in ways not captured by the date fixed effects. Interestingly, the results depicted in Table 2 hardly change when excluding the last two CPP events from the analysis. In addition, the March 30th event remains associated with a 14% reduction in peak demand, which is similar to the response to CPP events prior to the lockdown. The outlier is the April 28th event. Unfortunately, we cannot say whether the 4%-reduction in peak demand observed on that last CPP event is the result of the warm spring day, the Covid-19 lockdown, or a combination of both.

5.4 Response to feedback and social comparison treatment

The effect of one's own electricity consumption feedback with social comparison treatment is depicted in Table 4. This secondary treatment is implemented on half of the CPP treatment group on the last two CPP events (i.e., events 8 and 9 on March 30th and April 28th, respectively). It is empirically estimated by interacting the consumption feedback with social comparison treatment with the CPP treatment on the CPP day, differentiating for peak (with CPP) and non-peak hours. Results suggest the feedback with social comparison treatment is not associated with any significant change in electricity consumption relative to receiving the simple CPP event notification – estimates for $Treat \times Peak \times Day \times S.Comp$ and $Treat \times NPeak \times Day \times S.Comp$ are both insignificant. The absence of a significant effect is consistent with findings in some of the earliest studies using OPOWER in the US [Schultz et al., 2007, Nolan et al., 2008]. More recent studies have documented a small reduction in consumption in response to social comparisons, e.g., Ayres et al. [2012] and Allcott find a 2% reduction. These studies combine descriptive and injunctive norms to limit the boomerang effect, or regression to the mean of the consumers reducing more than the average – our treatment only relies on descriptive norms. Yet, other factors may drive our findings. First, the secondary treatment was implemented on the two warmest CPP

Table 4 Effect of consumption feedback with social comparison in the CPP treatment group on log of hourly electricity consumption. (1) and (2): Equation (1) both without and with temperature controls. (3): Equation (1) with treatment heterogeneity across households with or without electric cars. (4) and (5): Equation (2) with shoulder hours, both without and with electric car treatment heterogeneity. All specifications include household, date, and time of day (peak or non-peak) fixed effects. In columns (4) and (5), time of day fixed effects consist of peak, non-peak, or shoulder hours. (For each specification, the mean log electricity consumption (*ymean*) is 0.586.)

	(1)	(2)	(3)	(4)	(5)
$Treat \times P \times Day$	-0.140***	-0.140***	-0.137***	-0.140***	-0.137***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Treat \times NP \times Day$	-0.004*	-0.003	-0.005**	0.006**	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Treat \times P \times Post$	-0.026***	-0.018***	-0.017***	-0.018***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Treat \times NP \times Post$	-0.003*	-0.005***	-0.006***	-0.005***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
P	0.138***	0.143***	0.140***	0.161***	0.157***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
$Treat \times P \times Day \times S.Comp$	-0.001	0.010	0.010	0.013	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$Treat \times NP \times Day \times S.Comp$	0.012*	0.008	0.008	0.007	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$Treat \times P \times Day \times Ecar$			-0.057**		-0.057**
			(0.022)		(0.022)
$Treat \times NP \times Day \times Ecar$			0.020***		0.020**
			(0.007)		(0.008)
$Treat \times P \times Post \times Ecar$			-0.021**		-0.021**
			(0.009)		(0.009)
$Treat \times NP \times Post \times Ecar$			0.014**		0.014**
			(0.006)		(0.006)
$P \times Ecar$			0.059***		0.063***
			(0.006)		(0.007)
$Treat \times Shld \times Day$				-0.042***	-0.042***
				(0.003)	(0.003)
$Shld$				0.065***	0.064***
				(0.001)	(0.001)
$Treat \times Shld \times Day \times Ecar$					0.003
					(0.012)
$Shld \times Ecar$					0.017***
					(0.005)
temp	No	Yes	Yes	Yes	Yes
R^2	0.727	0.727	0.727	0.728	0.728
N	42,323,924	42,323,924	42,323,924	42,323,924	42,323,924

Note: Robust clustered standard errors at the household level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

events (Figure A3). More energy efficiency and lower demand leave less scope for reduction, which often cause social nudges to be ineffective [Carlsson et al., Forthcoming]. Indeed, the last CPP event reduced peak demand by only 4% (Table B2). Second, the last two CPP events further coincided with the Norwegian Covid-19 lockdown, which may have affected household response to social nudges. Third, the grid utility, due to technical challenges with computing one's own change in consumption, altered the original social comparison treatment. As a result, customers received a feedback message on their own consumption levels on the prior CPP event and on the day prior to that event, without an explicit change in one's own consumption, making the comparison with the average change in consumption in the rest of the treatment group less straightforward (see exact SMS language in section C.4). As a result, we cannot conclude whether Norwegian consumers do not respond to social comparison treatments or whether concerns with the treatment intervention – lack of direct comparison between the group and one's own response or poor timing due to warm weather – prevents us from observing an effect.

5.5 Consumer welfare analysis

CPP programs are typically designed to be ex ante revenue neutral for the utility. In our case, the grid utility did so by lowering the transmission charge outside the CPP events in the treatment group from 0.24 NOK/kWh to 0.05 NOK/kWh. As a result, the average consumer in the treatment group would pay exactly the same bill whether being subjected to the treatment or control pricing, assuming she maintains her consumption pattern as in the pre-treatment period (i.e., 0-price elasticity). However, consumers who consume relatively more (less) electricity during peak hours would face a higher (lower) bill under the treatment pricing, relative to the regular pricing faced by the control group. As Joskow and Wolfram [2012] point out, one of the main barriers to the adoption of time-varying pricing is the fear of large redistributions across customers. This can be the case if a small number of customers are very responsive, for example because they own electric vehicles, and capture most of the benefits from the CPP program at the expense of poorer households with less-elastic demand.

By observing actual electricity consumption in the treatment group during the experiment, we can compare the actual bill of these consumers with their counterfactual bill if they had received the control pricing, holding their new consumption pattern constant. Table 5 shows the difference and percentage difference between the actual and counterfactual bills for the mean and various percentiles of consumers in the treatment group. (For the full distribution, see Figure B1.)

Table 5 Average monthly difference and percentage difference between the actual and counterfactual bills of consumers in the treatment group. The mean monthly consumption in the treatment group is 1,783 kWh and amounts to 1,318 NOK.

Percentiles	Avg. diff. in monthly bill (in NOK)	Percentage diff.
p01	-315	-20.8 %
p05	-187	-13.9 %
p10	-136	-10.0 %
p15	-105	-7.9 %
p20	-87	-6.6 %
p25	-75	-5.7 %
p50	-37	-3.3 %
p75	-10	-1.2 %
p80	-5	-0.5 %
p85	1	0.1 %
p90	10	1.0 %
p95	27	2.8 %
p99	75	7.5 %
Mean	-52	-3.9 %

In Table 5, the average consumer in the treatment group save an average of 52 NOK per month (or USD5.8 using the November 2020 currency rate) over the five months of the experiment, which represents 3.9% of her average monthly bill. Examining the distribution of consumers who benefit or lose from the CPP program relative to the control pricing indicates that over 80% of consumers save money, while a little over 15% lose money. The top 1% save over 315 NOK on average per month (20.8% of their bill), while the bottom 1% lose over 75 NOK (7.5% of their bill).

To better grasp which groups of consumers save versus pay more under the CPP program, we divide our treatment households into four equal groups, denoted q1-q4, based on their average difference in monthly bill between CPP and the counterfactual control pricing. In Table 6, we calculate the average bill difference in each quartile (2nd column), and show the distribution of attributes of interest across the four quartiles (columns (3) - (11)). Table 6

Table 6 Distribution of treatment household characteristics across quartiles, q1-q4, as determined by the average monthly bill differences between the actual (treatment) and counterfactual (control) pricing. Bill diff.: Average monthly bill difference in each quartile in NOK. Q1-Q4: distributions of pre-treatment electricity consumption quartiles, Ecar: distribution of electric cars, IHD: distribution of IHD, $</>150\mathrm{m}^2$: distribution of housing size smaller/greater than $150\mathrm{m}^2$. Columns (3) - (11) sum to 100%. (Data source for $</>150\mathrm{m}^2$ and Fireplace is the summer 2019 survey distributed to all households having accepted the IHD offer.)

Qrtile	Bill diff.	Q1	Q2	Q3	Q4	Ecar	IHD	$<150\mathrm{m}^2$	$>150\mathrm{m}^2$	Fireplace
q1	-144	5	16	32	48	43	36	26	39	35
q2	-54	13	32	32	22	14	29	27	31	31
q3	-23	39	32	18	11	14	17	26	13	18
q4	14	43	19	18	18	30	18	21	17	17

shows that the lowest-user households (Q1) are more likely to belong to the top bill difference quartile (row 4) – 43% of households in Q1 pay on average 14 NOK more per month, while 48% of the highest users (Q4) save an average of 144 NOK/month (bottom bill difference quartile). Interestingly, households with electric cars are most likely to be found in the bottom quartile (saving an average of 144 NOK/month) and in the top quartile (losing an average of 14 NOK/month). It may be due to the fact that electric car households are both high-electricity users, with more scope for adjustment, and are also characterized by higher incomes, possibly less inclined to make changes to their consumption habits. Indeed, the correlation between having an electric car and belonging to the highest consumption quartile in the pre-treatment period (Q4) is 0.3, while it declines monotonically to -0.1 for the lowest consumption quartile (Q1). Households with IHD are unambiguously more likely to save under the new CPP program, likely due to their high consumption and interest in electricity consumption and price information. Drawing from a survey of the consumers who received and accepted an IHD offer prior to the CPP program (representative of IHD households but not necessarily of our sample; last three columns), households with larger homes (above $150\mathrm{m}^2$) or who have access to wood-heating are more likely to benefit from the CPP program.

6 Conclusions

This paper documents household electricity consumption response to critical peak pricing (CPP). Leveraging detailed hourly electricity consumption data and in partnership with a grid utility in Norway, we implement an RCT to estimate the effect of grid CPP on peak and non-peak consumption across groups of consumers. This is the first study that specifically examines time-varying grid pricing to address grid transmission congestion. As the retail electricity spot price already reflects the real marginal cost of electricity generation, the pricing of grid transmission capacity constraints stands as the remaining major cause of pricing inefficiency in Norway. Second, along with Fowlie et al. [2017], this is the first study to feature a default enrollment design with an opt-out option. This matters for the estimation of demand elasticities that are representative of the broader population since it is well-known that opt-in studies suffer from considerable sample selection bias [Harding and Sexton, 2017]. Last, our treatment does not rely on the installation of real-time consumption IHD, suggesting that CPP may be readily implementable without the need of additional investments from regulators or utilities. Our findings reveal that all consumer groups reduce their peak demand in response to CPP events, assuaging fears that CPP programs lead to large redistributions among consumer groups. Unfortunately, we cannot satisfactorily conclude whether peak demand may be further reduced by combining CPP events with nudging and social norms. Further research is needed in this area.

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Internet Appendix

A Additional data description

Table A1 Descriptive statistics for the summer 2019 survey distributed to all households who accepted the IHD offer in 2017.

	Treatment		Control	
	Mean	SD	Mean	SD
# members in HH	2.72	(1.19)	2.77	(1.24)
1	0.13	(0.34)	0.14	(0.35)
2	0.38	(0.49)	0.36	(0.48)
3	0.19	(0.40)	0.19	(0.39)
4	0.20	(0.40)	0.19	(0.40)
5+	0.09	(0.29)	0.11	(0.32)
Housing type				
Detached house	0.78	(0.41)	0.80	(0.40)
Semi-detached/townhouse	0.16	(0.37)	0.13	(0.34)
Other	0.05	(0.22)	0.07	(0.26)
Surface area (m2)	180.97	(58.31)	181.88	(59.55)
<50	0.01	(0.09)	0.00	(0.06)
51-100	0.16	(0.37)	0.18	(0.38)
101-150	0.33	(0.47)	0.30	(0.46)
151-200	0.26	(0.44)	0.29	(0.45)
201-250	0.16	(0.37)	0.14	(0.35)
>251	0.07	(0.26)	0.09	(0.28)
Building year	1975.85	(31.83)	1972.28	(27.65)
Has been renovated (0/1)	0.59	(0.49)	0.59	(0.49)
Fireplace (0/1)	0.82	(0.38)	0.81	(0.39)
# cars	1.75	(0.67)	1.75	(0.68)
0	0.01	(0.12)	0.01	(0.09)
1	0.33	(0.47)	0.36	(0.48)
2	0.54	(0.50)	0.50	(0.50)
3+	0.11	(0.32)	0.13	(0.33)
Electric or plug-in car (0/1)	0.15	(0.36)	0.12	(0.33)
Education				
High-school	0.46	(0.50)	0.39	(0.49)
Bachelor degree	0.29	(0.46)	0.34	(0.47)
Graduate degree	0.25	(0.43)	0.27	(0.44)
N	324		627	

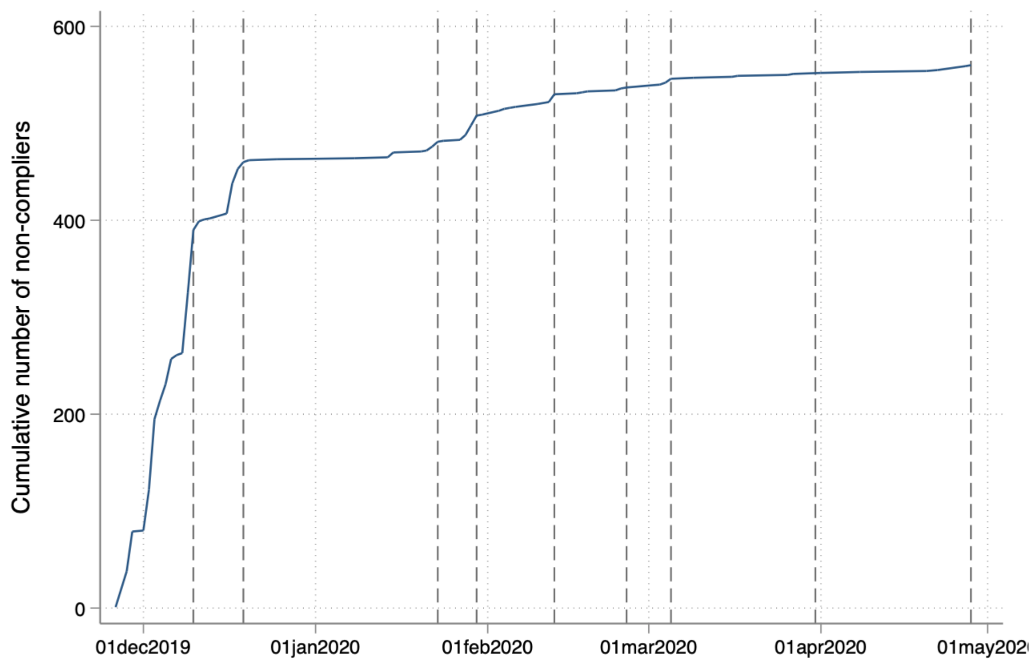


Figure A1 Cumulative distribution of the number of non-compliers. The nine CPP events are depicted as dashed lines. By the end of the intervention, a total of 560 customers had requested to be taken out of the treatment group. Of those, 390 (70%) did so prior to the first CPP event.

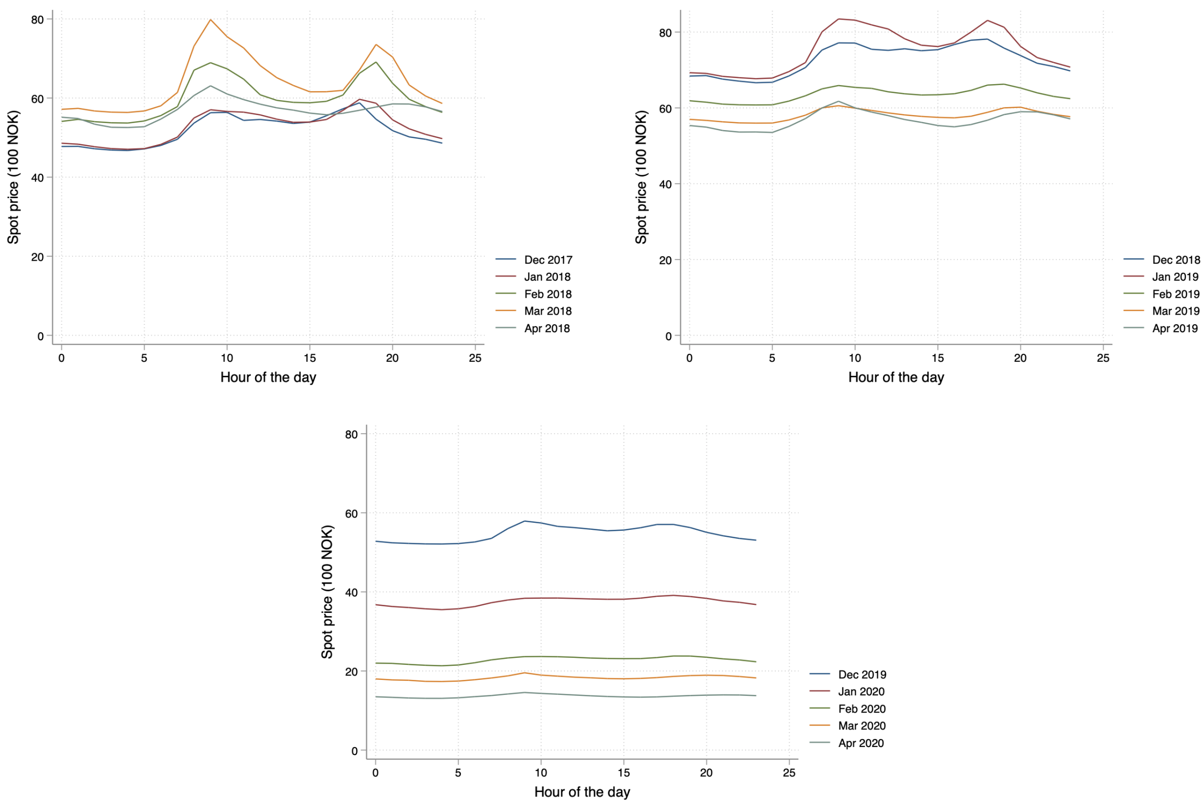


Figure A2 Average hourly spot price by month (December to April) for the winters 2017-2018 (top left), 2018-2019 (top right), and 2019-2020 (bottom).

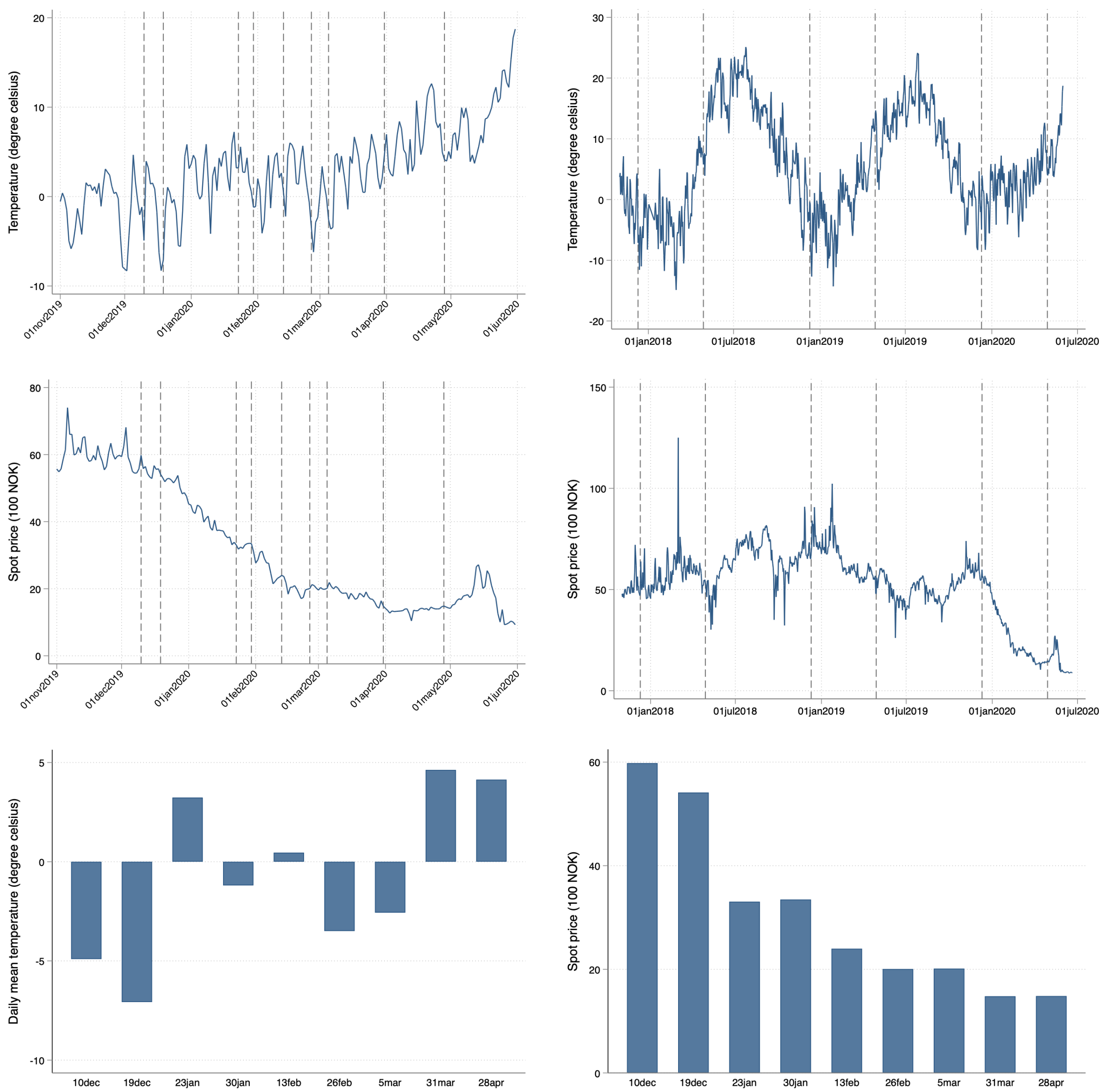


Figure A3 Average daily temperature and spot price. Top panels show temperature and middle panels show the spot price, while left panels show the November 2019 to May 2020 period with the nine CPP events depicted as dashed lines, and right panels show the November 2017 to May 2020 period with 10 December and 28 April depicted as dashed lines in each year. Bottom panels show temperature (left) and spot price (right) for each of the nine CPP events.

B Additional results

For each specification in Table B1, CPP events are associated with a 0.15-log point reduction in peak electricity consumption in the treatment group relative to the control group. This is slightly higher than in the model with household fixed effects (Table 2). Again, across all specification, there is no sign of load shifting to non-CPP hours, but rather a small persistent reduction effect on the two days following a CPP event.

Treatment heterogeneity across households with or without electric cars is shown in columns (3) and (5). Although electric car households consume more electricity (the coefficient for $Ecar$ is 0.43 log points), their response to CPP is not significantly different from non-electric car households for specifications without household fixed effects.

Load shifting to shoulder hours is shown in columns (4) and (5), without and with allowing for heterogeneity across electric car households, respectively. Results in column (4) suggest that the reduction in electricity consumption outside the peak hours on a CPP day largely took place in the shoulder hours, with a reduction of 0.042 log points for the treatment group relative to the control group. The reduction in electricity consumption in the shoulder hours is not significantly different when examining the response of electric car households in the treatment group ($Treat \times Shld \times Day \times Ecar$; column (5)), consistent with Table 2 with household fixed effects.

Table B1 Effect of CPP events on log of hourly electricity consumption, without household fixed effects. (1) and (2): Equation (1) both without and with temperature controls. (3): Equation (1) with treatment heterogeneity across households with or without electric cars. (4) and (5): Equation (2) with shoulder hours, both without and with electric car treatment heterogeneity. All specifications include date and time of day (peak or non-peak) fixed effects. In columns (4) and (5), time of day fixed effects consist of peak, non-peak, or shoulder hours.

	(1)	(2)	(3)	(4)	(5)
$Treat \times Peak \times Day$	-0.153***	-0.152***	-0.151***	-0.152***	-0.151***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$Treat \times NPeak \times Day$	-0.015	-0.016	-0.019	-0.006	-0.010
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
$Treat \times Peak \times Post$	-0.039***	-0.031**	-0.033**	-0.031**	-0.032**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$Treat \times NPeak \times Post$	-0.016	-0.018	-0.022	-0.018	-0.022
	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)
$Peak$	0.138***	0.143***	0.140***	0.161***	0.157***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
$Ecar$			0.429***		0.425***
			(0.023)		(0.023)
$Treat \times Peak \times Day \times Ecar$			-0.024		-0.024
			(0.038)		(0.038)
$Treat \times NPeak \times Day \times Ecar$			0.054		0.053
			(0.034)		(0.035)
$Treat \times Peak \times Post \times Ecar$			0.012		0.012
			(0.033)		(0.033)
$Treat \times NPeak \times Post \times Ecar$			0.048		0.048
			(0.034)		(0.034)
$Peak \times Ecar$			0.059***		0.063***
			(0.006)		(0.007)
$Treat \times Shld \times Day$				-0.042***	-0.042***
				(0.003)	(0.003)
$Shld$				0.065***	0.064***
				(0.001)	(0.001)
$Treat \times Shld \times Day \times Ecar$					0.002
					(0.011)
$Shld \times Ecar$					0.017***
					(0.005)
$temp$	No	Yes	Yes	Yes	Yes
R^2	0.046	0.046	0.062	0.047	0.062
N	42,323,924	42,323,924	42,323,924	42,323,924	42,323,924

Note: Robust clustered standard errors at the household level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B2 Effect of CPP on log of hourly electricity consumption for each one of the nine CPP events. For each CPP event, electricity consumption covers the period starting three days after the previous CPP event (or December 1 2019 for the first CPP event) and up to two days after a CPP event. All specifications use equation (2) with shoulder hours and electric car treatment heterogeneity. (Results without electric car treatment heterogeneity are quantitatively similar.) All specifications include household, date, and time of day (peak, non-peak, or shoulder hours) fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Treat \times Peak \times Day$	-0.163***	-0.125***	-0.139***	-0.165***	-0.159***	-0.157***	-0.131***	-0.155***	-0.040***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$Treat \times NPeak \times Day$	-0.012***	-0.001	-0.000	0.007**	0.010***	0.027***	0.009**	0.031***	-0.038***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
$Treat \times Peak \times Post$	-0.019***	-0.013**	-0.017***	-0.008*	-0.006	-0.023***	-0.017***	-0.005	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
$Treat \times NPeak \times Post$	-0.024***	-0.006	-0.008**	-0.010***	-0.006*	-0.001	-0.006*	-0.007*	-0.019***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
$Peak$	0.165***	0.166***	0.179***	0.179***	0.172***	0.155***	0.151***	0.128***	0.088***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Treat \times Peak \times Day \times Ecar$	-0.092***	-0.058**	-0.051	-0.079**	-0.065**	-0.072**	-0.026	-0.033	-0.035
	(0.032)	(0.029)	(0.032)	(0.033)	(0.031)	(0.031)	(0.033)	(0.031)	(0.032)
$Treat \times NPeak \times Day \times Ecar$	0.005	0.003	0.054***	0.015	0.029**	-0.014	0.041***	-0.003	0.044**
	(0.015)	(0.016)	(0.016)	(0.014)	(0.013)	(0.017)	(0.015)	(0.015)	(0.018)
$Treat \times Peak \times Post \times Ecar$	0.006	-0.044*	0.025	-0.045**	-0.049**	-0.071***	0.019	0.019	-0.008
	(0.017)	(0.022)	(0.019)	(0.018)	(0.021)	(0.021)	(0.019)	(0.017)	(0.020)
$Treat \times NPeak \times Post \times Ecar$	0.011	0.000	0.032**	0.004	0.018	-0.012	0.052***	-0.010	0.022
	(0.012)	(0.015)	(0.013)	(0.011)	(0.012)	(0.016)	(0.012)	(0.011)	(0.014)
$Peak \times Ecar$	0.067***	0.057***	0.059***	0.070***	0.073***	0.038***	0.061***	0.064***	0.072***
	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)
$Treat \times Shld \times Day$	-0.032***	-0.017***	-0.047***	-0.050***	-0.058***	-0.085***	-0.052***	-0.069***	0.075***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Shld$	0.072***	0.084***	0.084***	0.064***	0.065***	0.050***	0.056***	0.033***	0.039***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$Treat \times Shld \times Day \times Ecar$	0.025	0.039*	-0.034	0.007	0.012	0.006	0.024	-0.019	-0.028
	(0.023)	(0.022)	(0.025)	(0.020)	(0.021)	(0.023)	(0.020)	(0.024)	(0.027)
$Shld \times Ecar$	0.027***	0.019***	0.022***	0.024***	0.021***	0.004	0.014**	0.003	0.020***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
$temp$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$ymean$	0.773	0.765	0.662	0.634	0.663	0.614	0.684	0.530	0.310
R^2	0.808	0.805	0.771	0.795	0.787	0.772	0.797	0.748	0.691
N	3,301,324	2,476,042	9,715,194	1,925,169	3,849,362	3,941,441	2,290,540	7,134,668	7,690,184

Note: Robust clustered standard errors at the household level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

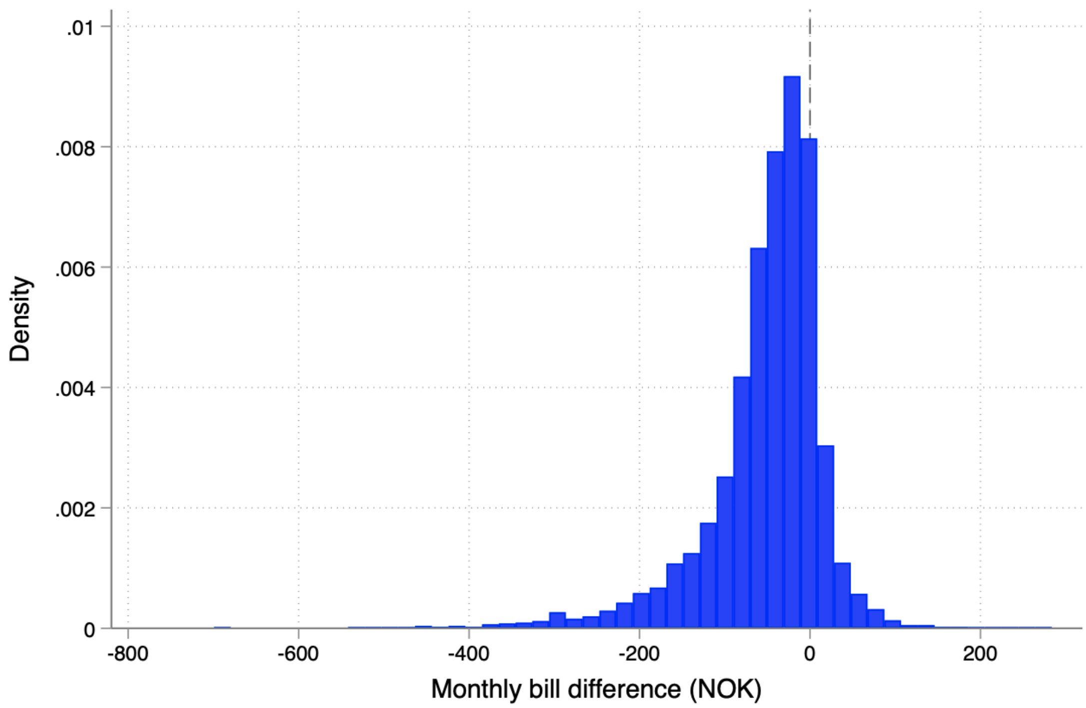


Figure B1 Distribution of the average monthly bill difference (in NOK) between the actual bill (with CPP) and the counterfactual bill (with control pricing) for consumers in the treatment group. The dashed line indicates no difference.

C Communication with customers in treatment group

C.1 Timeline overview

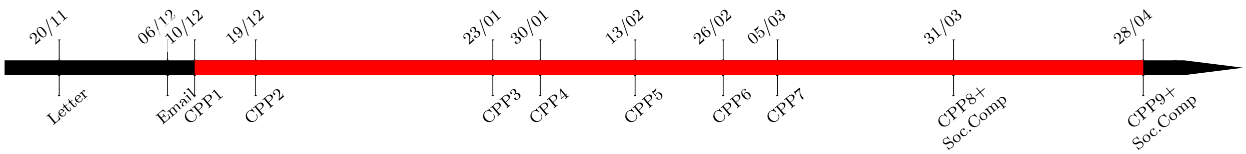


Figure C1 Timeline overview of the CPP intervention and communication with the customers in 2019-2020. The CPP intervention, depicted in red, consists of nine CPP events that took place between December 10 2019 and April 28 2020. The last two CPP events also featured a social comparison instrument. Sample selection and randomization was completed on October 23 2019, prior to the experiment.

C.2 First contact: Information sent in the mail in November

C.2.1 Letter about participation in the CPP program, with opt-out

Ringerikskraft
Nett

Plass til adresse

Pilotprosjekt for ny nettleiemodell

Hei,

Din husstand er tilfeldig plukket ut til å delta i vårt pilotprosjekt for ny nettleiemodell. Sammen med 4000 av nettkundene våre får du fra 1. desember mulighet til å være med å teste og gi tilbakemeldinger på det som kan bli fremtidens nettleiemodell.

Hvorfor?

Måten vi bruker strøm på, og hvor mye strøm vi har behov for, er i endring. Elektrifisering av samfunnet, det vil si at stadig mer går på strøm, er et viktig og positivt klimatiltak. Ved økt strømbruk belaster vi kapasiteten i nettet stadig mer. Fortsetter vi å øke forbruket vil det være behov for å øke kapasiteten, en investering som er kostbar og som øker nettleien. Målet vårt er at denne nye modellen skal hjelpe oss alle med å få et mer bevisst forhold til hvordan vi bruker strøm, slik at vi unngår kapasitetsutfordringer og unødige kostnadsøkninger.

Hva betyr dette for meg?

Som pilotkunde får du bedre mulighet til å spare nettleie enn med tidligere prismodell. Det vil i praksis si at du, gjennom et bevisst forhold til eget strømforbruk, kan påvirke hvor mye du bruker og hvor mye strømregningen kommer på. Du får også mulighet til å gi tilbakemeldinger og innspill underveis slik at vi sammen kan skape en god modell som kan bidra til at vi unngår store investeringer i fremtiden. Om vi klarer å utnytte den gode kapasiteten vi allerede har gjennom hele døgnet, vil vi sammen klare å holde igjen investeringer som også påvirker nivået på nettleien.

Hva skjer videre?

10 dager i året blir du varslet på SMS i forkant av en dag med peaktimer mellom klokken 16.00 og 22.00. Dette gjelder hovedsakelig i vintermånedene hvor vi bruker mest strøm og kapasiteten er minst. Dersom du er bevisst strømforbruket ditt i peaktimene og gjør noen sparetiltak vil du spare penger. Om du ikke gjør noen tiltak og bruker strøm som vanlig vil nettleien koste omtrent like mye som før. Bruker du mer strøm enn du pleier i peaktimene må du belage deg på at det vil koste deg ekstra.

Med varsling i forkant av dager med peaktimer håper vi at vi kan oppfordre og inspirere til å bruke mindre strøm når kapasiteten er begrenset og prisene er høyere. Vi håper du vil bli med oss videre i prosjektet og hjelpe oss med å bygge fremtidens prismodell! Gjennom deltagelse i prosjektet gjør du oss i bedre stand til å levere bedre tjenester fremover, samtidig som du påvirker din egen strømregning.

Kontaktinformasjon på baksiden →

Ringerikskraft Nett AS | Besøksadresse: Hvervenmoveien 33, 3511 Hønefoss | Postadresse: Postboks 522, 3504 Hønefoss |
kundeservice@ringerikskraftnett.no | 32 11 96 50 | Org.nr: 987 626 844 | **ringerikskraftnett.no**

Kontakt oss

Har du har spørsmål eller kommentarer til prosjektet eller nettleiemodellen – ikke nøl med å ta kontakt!
Du kan ta kontakt med oss når som helst i pilotperioden, så hjelper vi deg med det du måtte lure på.

Om du ikke ønsker å delta ber vi deg kontakte oss på 32 11 96 72, så vil kundesenteret vårt hjelpe deg.

Du kan også lese mer om prosjektet på www.ringerikskraftnett.no/pilot

Åpningstider
Ring kundesenteret på 32 11 96 72
Vi holder åpnet mandag til fredag kl. 08:00 til 16:00
Fra 25.11 til 6.12 har vi utvidet åpningstid på telefon 32 11 96 72 til klokken 18:00

Med vennlig hilsen

Live Dokka
Prosjektleder for pilotprosjektet

Jan-Erik Brattbakk
Nettsjef Ringerikskraft Nett

Ringerikskraft Nett AS | Besøksadresse: Hvervenmoveien 33, 3511 Hønefoss | Postadresse: Postboks 522, 3504 Hønefoss |
kundeservice@ringerikskraftnett.no | 32 11 96 50 | Org.nr: 987 626 844 | **ringerikskraftnett.no**

English translation

Your household has been randomly selected to participate in our pilot project for a new grid rental model. Together with 4,000 of our customers, you will from December first have the opportunity to take part in testing and giving feedback on what may be the utilities grid rental model of the future.

Why? The way we use electricity and how much electricity we need is changing. Electrification of society, ie, more and more electricity, is an essential climate measure. With increased power consumption, we are increasingly straining the capacity of the grid. If we continue to increase consumption, there will be a need to increase capacity. This costly investment increases grid rent. Our goal is for this new model to help us all have a more conscious relationship with how we use electricity to avoid capacity challenges and unnecessary cost increases.

What does this mean for me? As a pilot customer, you get a better opportunity to save on grid rent than with the previous pricing model. In practice, this means that you, through a conscious relationship to your electricity consumption, can influence the electricity bill costs. You also get the opportunity to give feedback and input along the way so that we can create a better model to avoid large investments in the future. If we manage to utilize the capacity we already have throughout the day, we will be able to hold back investments that will affect the grid rent.

What happens next? Nine days during the year, you will be notified by SMS in advance of a peak day with peak hours between 16.00 and 22.00. This applies in the winter months where we use the most electricity, and the capacity is stretched. If you are aware of your electricity consumption during peak hours and take some saving measures, you will save money. If you do not take any measures and use electricity as usual, the grid rent will cost about as much as before. If you use more electricity than you usually do during peak hours, you have to be aware that it will increase your cost.

With notice in advance of days with peak hours, we hope that we can encourage and inspire to use less electricity when capacity is stretched, and prices are high. We hope you will join us in the project and help us build the future pricing model! By participating in the project, you enable us to deliver better services in the future, at the same time as you influence your electricity bill.

C.2.2 Two-sided brochure

Ringerikskraft Nett

NY PRISMODELL

Bruk mindre når det koster mer

Med bevisst strømbruk kan vi unngå begrenset kapasitet og kostnadsøkninger.

UTVIKLINGEN

Elektrifiseringen av samfunnet

Hvordan kom vi hit?
Elektrifiseringen fører til økt belastning: Klokken 16.00 kommer alle hjem fra jobb og skole. Elbilene lades, huset varmes opp, du tar en dusj, tørketrommel og oppvaskmaskinen går og middagen står i ovnen. Når alle bruker mye strøm samtidig, kan det enkelte dager oppstå kapasitetsutfordringer.

Økt forbruk belaster kapasiteten i nettet – og kapasiteten er ikke uendelig.
Dette gjelder i hovedsak på kalde dager og i ettermiddags-timene. Fortsetter vi å øke forbruket på disse dagene, og om alle f.eks. lader elbilen på ettermiddagen, så vil det være behov for å gjøre store investeringer. Investeringer i økt kapasitet er kostbart og vil øke nettleien.

Bedre sammen

Hva kan vi gjøre sammen for å unngå dyre investeringer? Sammen med kundene våre vil vi undersøke hvordan vi kan bygge opp best mulig ordning for nettleie for både kundene, samfunnet og nettselskapet. Om vi i fellesskap blir mer bevisst strømbruken vår og fordeler den mer utover døgnet, kan vi unngå kapasitetsutfordringer.

Peaktimer og prising

Jo mer strøm du bruker, jo høyere blir strømregningen. Slik er det i dag, og slik vil det naturlig nok alltid være. Med den nye modellen er det lettere å spare penger enn tidligere.

Tar du hensyn til peaktimene som kommer 10 dager i året og justerer strømbruken, så påvirker du direkte sluttsummen på regningen. Forskjellen mellom en vanlig ettermiddag og en ettermiddag med peaktimer kan se slik ut:

En vanlig tirsdag i november uten peaktimer (off peak) koster strømmen 1 kr/kWh*. Ettermiddagen etter er det peaktimer mellom 16.00 og 22.00. Da koster strømmen 10 kr/kWh.*

Kan du utsette å bruke tørketrommelen og lade elbilen midt i peaktimene 10 dager i året? Da vil du spare penger og samtidig sørge for mindre belastning på strømnettet når kapasiteten er minst.

Peaktimene vil alltid være varslet, og du kan selv velge om du ønsker å gjøre tiltak eller ikke. Siden nettleieprisen går ned på alle andre dager enn peakdagene, så vil du fortsatt ende opp med tilnærmet lik total nettleie som tidligere modell dersom du ikke ønsker å flytte forbruket.

Om du bruker tørketrommel 1 time og lader elbilen på 7 kW i tre timer bruker du omtrent 23 kWh.

Off peak vil det koste **23 kr*** I **peaktimene** vil det koste **230 kr***

**Prisen på 1 kr/kWh og 10 kr/kWh er en gjennomsnittspris på både strøm og nettleie. Årsaken er at strømprisen varierer fra time til time. Nettleien varier kun mellom vanlig pris (off peak) og peaktimer.*

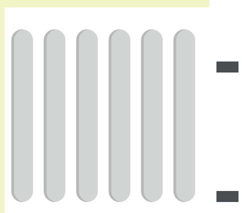
Ring 32 11 96 72 for henvendelser om pilotprosjektet. Les mer på **ringerikskraftnett.no/pilot**

Ringerikskraft
Nett

Nyttige sparetips

De aller fleste kan tenke seg å spare penger på å bruke mindre strøm, men er usikker på hvordan de gjør det samtidig som de skal få hverdagen til å gå rundt. Her er noen tips til sparing som skal opprettholde komforten.

Reduser mengden strøm til oppvarming fra panelovner og varmekabler



✓ Kan du skru ned temperaturen en grad eller to i rom du ikke bruker så ofte? Eller programmere ovnene til bestemte tidspunkter av døgnet?

✓ Med varmepumpe kan du få mer varme med mindre strøm.

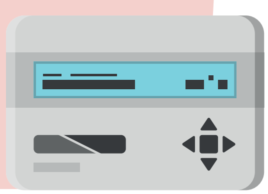
✓ På kalde dager kan det være lurt å fyre med ved om man har mulighet til det.

Kan du styre varmen?

✓ Kan du varme opp huset litt før du kommer hjem fra jobb? Da kan du senke temperaturen litt på ettermiddagen når strømmen gjerne er litt dyrere enn på dagtid. Og kanskje også holde varmen med vedfyring.

✓ En del varmepumper kan styres. Sjekk om du kan programmere din til bestemte tider av døgnet.

✓ Skal du ha ny varmtvannsbereder? Det kommer stadig nye løsninger på markedet som er smartere og mer effektive enn tidligere modeller.



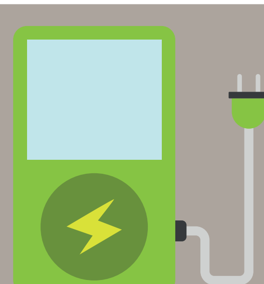
Alle trenger varmtvann, men klarer du å spare litt?

✓ Å fylle et helt badekar bruker mye mer varmtvann enn en dusj. Kutter du ned antall dager med badekar, så kan du spare mye på strømregningen.

✓ Kan noen av dusjene i løpet av uken gjøres unna på noen få minutter fremfor en halvtime? Da er det mye å spare!

✓ Har du tatt oppvasken fremfor å sette i gang oppvaskmaskinen for å spare strøm? Det er ikke sikkert det var lønnsomt. Oppvaskmaskiner er energieffektive, og man bruker gjerne mye varmtvann ved oppvask for hånd. Husk heller å fylle opp maskinen før du starter den.

Lad elbilen på natten



✓ Elbilen trekker mye strøm når den lader. Lad gjerne på natten når resten av strømforbruket er lavt.

C.3 Second contact: Email sent on December 6th, one week prior to the first CPP event

Hei,

Takk for at du er deltaker i prosjektet vårt for ny prismodell. Sammen med 4000 av kundene våre tester vi ut om en prismodell tilpasset etterspørsel og kapasitet i strømnettet kan gjøre oss mer bevisst egen strømbruk. Det kan bidra til at vi unngår kapasitetsutfordringer noen få timer i døgnet, og at vi utnytte den gode kapasiteten vi har totalt sett gjennom døgnet.

Kaldere dager gir økt forbruk

Det går mot kaldere tider, og vi ser at forbruket i nettet øker. Vi forbereder oss derfor på at det kommer en dag med peaktimer mellom kl. 16 og 22 neste uke. I disse timene er prisen på nettleien høyere, og ved å gjøre noen sparetiltak kan du både spare penger og fristille kapasitet i strømnettet. Alle andre timer som ikke er peaktimer er prisen lavere enn den vanlige nettleien.

Vi varsler på SMS dagen før slik at du og din husstand er forberedt og har mulighet til å planlegge. Som en ekstra påminnelse sender vi også en SMS rett før timene med høyere nettleiepris starter.

I desember vil det bli gjennomført to dager med peaktimer før jul, og deretter blir det to dager hver måned til og med april.

I brevet du har fått i posten og på nettsidene våre har vi lagt ut noen sparetips og priseksempler. Det betyr ikke at du skal bekymre deg for å bruke strøm som normalt i disse timene, men for de av dere som ønsker å spare og ønsker å vite mer om hvilke tiltak som betyr mest, så er det verd å lese. Og husk, bruker du strøm som vanlig vil den totale strømregning bli omtrent lik som du er vant til.

Sparetips til peaktimer

Kan du redusere temperaturen i rom du ikke bruker så ofte eller programmere oppvarmingen til bestemte tidspunkter på døgnet?
Kan du fyre med ved?
Ta en kort dusj fremfor å fylle hele badekaret.
Kan du planlegge noe av klesvasken utenom?
Kan du lade elbilen på natta?

Elsikkerhet er viktig for oss. Sparetipsene våre er ikke en oppfordring til å flytte alt forbruk til natten. Om du har elbil og lader den hjemme er det viktig at du benytter godkjent ladepunkt for elbil.

Ta kontakt med oss ved spørsmål og tilbakemeldinger. Dine innspill er viktige for oss, og blir en del av prosjektvurderingen.

Åpningstider

Kundesenteret holder åpent mandag til fredag kl. 08:00 til 16:00

Tlf. **32 11 96 72**

C.4 SMSs sent to the treatment group

Figure C2 Example of SMS sent one day prior to a CPP event (left) and SMS reminder sent on the day of the CPP event (right). English translation: (Left) Hi, tomorrow there will be peak hours 16h-22h. You will save money if you reduce your electricity consumption during these hours. We care about safety - thus we do not encourage you to shift your electricity consumption to when you are asleep. Best regards, Ringerikskraft Nett. (Right) Hi, let us remind you about peak hours from 16-22 today. Here you can find tips on how to save electricity www.riknett.no/pilot. Best regards, Ringerikskraft Nett.

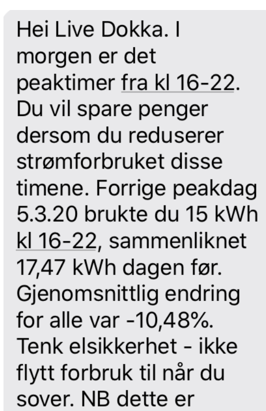


Figure C3 Example of SMS sent one day prior to a CPP event with information feedback + social comparison. English translation: Hi, tomorrow there will be peak hours 16-22h. You will save money if you reduce your electricity consumption during these hours. On the previous peak day on day/month you used 15 kWh from 16-22h, compared to 17.47 kWh on the day prior to that peak day. The average change in consumption for all customers was -10,48%. We care about safety - thus we do not encourage you to shift your electricity consumption to when you are asleep. Best regards, Ringerikskraft Nett